12-10-2020 1:30 PM

A novel spatio-temporal examination of children's accessibility, exposure, and engagement to parks and recreation spaces in Middlesex-London, Ontario

Malcolm K. Little, *The University of Western Ontario*

Supervisor: Gilliland, Jason, *The University of Western Ontario*

A thesis submitted in partial fulfillment of the requirements for the Master of Science degree in Geography

Abstract

Canadian children are increasingly spending their free time engaged in sedentary activities indoors, rather than in outdoor environments such as parks and recreation spaces. Research has confirmed that parks and recreation spaces provide amenities that promote improved physical, cognitive, and social health among children. However, accurately measuring children's levels of interactions with these spaces is poorly understood in children's geography research, especially as it relates to the complexities of individual children's living situations.

The purpose of this thesis is to improve on the measurement of children's level of interactions with parks and recreation spaces, and to examine attributes of children associated with levels of interactions. To meet the study objectives, this research utilized survey data and GPS logs from participants ages 9-14 years, recruited throughout southwestern Ontario for a mixed-methods project conducted in 2010-2013, combined with a high-resolution GIS dataset of environmental factors. Sociodemographic characteristics gathered from surveys and GPS tracks of the participants were linked to the GIS dataset, which included regional parks-and recreation data. Home locations and daily GPS tracks were examined through an Accessibility-Exposure-Engagement framework, to compare measures for estimating levels of interactions with parks and recreation spaces. Statistics revealed relationships between children's sociodemographic attributes and levels of exposure/engagement with specific parks and recreation amenities. Hierarchical linear regression modelling, with blocks representing levels containing sociodemographic variables, assessed the influence of children's individual, interpersonal, social, and built-environment characteristics on their proportion of free time in parks and recreation spaces.

Results suggest measures of proximity to parks and recreation spaces do not represent actual use, frequency of exposure, and duration of engagement to them by children. A child's gender, visible minority status, and neighbourhood urbanicity, are associated with the proportion of free time in parks and recreation spaces. Moving forward, children's geography research should utilize the most accurate and/or practical methods for estimating children's use of health-positive environments such as parks and recreation.

Keywords: accessibility; children; engagement; exposure; GIS; GPS; parks and recreation; sociodemographics

Summary for Lay Audience

Canadian children are spending more free time indoors, inactive, and not engaged in sports and recreation activities. These activities are supported by parks and recreation facilities, which can promote physical, mental, and social well-being among children. Previous research has struggled to accurately measure how often children are engaged in these places. Also poorly understood is the level of influence social and economic aspects of children's households have on their use of parks and recreation facilities.

This thesis compares methods that measure children's use of parks and recreation facilities and detects traits of children associated with use. Together with geographic data of southwest Ontario, this thesis used both household survey and GPS data from volunteers aged 9-14 years. The volunteers were recruited from schools throughout southwest Ontario. That data was joined to regional data containing locations and types of parks and recreation facilities.

Along with their daily GPS tracks, the volunteer's home locations were used to uncover what places were close by, what places they went to, and how much free time they spent in them. This approach revealed the most accurate way to measure which parks and recreation facilities are accessible from children's homes. It also revealed how much free time children spend in them, and which social and economic aspects of children's lives relate to the type of places they go to and for how long.

In the last several years, there has been shocking declines in Canadian children's health and activity levels. Given this, geography research on children must use more accurate means for determining what drives children to use healthy places like parks and recreation facilities. This thesis provides evidence for improving the accuracy of geography research involving children. It also helps inform parks and recreation policies seeking to provide better accessibility and use.

Table of Contents

List of Tables

List of Figures

List of Appendices

1 Introduction

1.1 Research Context

In August 2020, Children First Canada, in conjunction with the University of Calgary, released a report outlining numerous growing threats to the well-being of Canadian children (C. F. Canada, 2020). This report was informed by yearly ParticipACTION reports focusing on the poor physical activity levels of Canadian children that have persisted over the last decade (ParticipACTION, 2020). In particular, Canadian children fare poorly in measurable health-related outcomes. This startling trend is corroborated in scholarly studies that found decreases in numerous positive health outcomes, such as moderate-vigorous physical activity (MVPA) levels (Molnar et al., 2004; Timperio et al., 2015; Button et al., 2020), social and community cohesion (Wood et al., 2013), resilience (Brussoni et al., 2020; Chaudhury et al., 2019), and cognitive performance (Kweon et al., 2017)

Parks and recreation spaces offer a lifeline of health-positive environments with an array of potentially engaging activities for children. Many of the potential activities that parks and recreation spaces provide children can help mitigate or reverse the aforementioned declines in overall health. Potential for activities, however, does not merely involve clinical measures of health outcomes. Rather, activities and health are interwoven within spaces. Therefore, measures of accessibility to health-positive environments factor into improving health outcomes, and thus factor into the overall well-being of Canadian children.

Environments children can interact with have considerably evolved over the last half-century. In his book *Bowling Alone* (2000), Robert Putnam describes how the range an average North American child is allowed by their parents/guardians to independently explore outside their home has decreased from 2500m in 1950 to 500m in 2000. This permitted distance for children to independently roam has declined further in recent years (Carver et al., 2014; Schoeppe et al., 2016). Additionally, the number of activities and venues permitted by parents/guardians for children has also decreased over the last half-century (Molnar et al., 2004; Putnam, 2000). This trend of reduced spatial independence coupled with rising levels of adverse health outcomes is worrisome for Canadian children and their parents/guardians.

One of the few remaining types of outdoor spaces that children are allowed to independently engage in are parks and recreation spaces (Clark et al., 2019; Dunton et al., 2014; Putnam, 2000; Webber et al., 2008). For children, there are numerous health benefits associated with parks and recreation spaces, such as opportunities for activities that improve physical fitness (Maddison et al., 2010; Mitchell, 2016; Krenn et al., 2011), community-based activities that improve social connectedness (Pearson et al., 2017; Wray et al., 2020; Yip et al., 2016), unstructured play that promotes resilience (Brussoni et al., 2017), and natural settings that improve mental well-being (Tillmann et al., 2018; Wu et al., 2011).

In Canada, parks and recreation spaces and their installed amenities are driven by municipal and regional policies. Via zoning and development plans, these policies influence the spatial configuration of such spaces (Cullingworth, 2017). Maximizing accessibility to parks and recreation amenities for residents is a key driver in municipal planning (Parks Canada, 1994; Cullingworth, 2017); many policies also seek to address accessibility to parks and recreation amenities amongst vulnerable segments of the population, most notably children (Alexander et al., 2013; Siu, 2013).

Regardless of planning centered on parks and recreation spaces, and the policies driving their development and maintenance, research linking accessibility to policy is sporadic, and existing research is inconsistent in its methods and outcomes. There exists a need for scholarship to evaluate the effectiveness of policy specifics regarding parks and recreation spaces. Parks and recreation spaces are a significant part of the physical environment, thus examination of their spatial characteristics is apropos, especially considering precise locational/spatial data is readily available on the amenities provided in parks and recreation spaces (e.g. municipal/regional open data catalogues). In contrast, there is a dearth of precise locational/spatial data that examines whether children are objectively exposed to parks and recreation spaces.

Research measuring children's interactions with their environments can be broadly categorized into accessibility, exposure, and engagement factors (Tillmann et al., 2018; Wray et al., 2020). Accessibility factors deal with classes of environments and land uses that are within a specific range – typically along a network path or Euclidean distance – of a child's home, school, or community locations (Clark et al., 2019; Clark et al., 2018; Pratt et al., 2004). Accessibility can be measured in a Geographic Information System (GIS) by utilizing buffers of varying distances, then measuring features intersecting or contained within the buffers (Amoly et al., 2015; Sadler & Gilliland, 2015; Tallis et al., 2018). Research that utilizes buffers to measure features in children's environments are frequently linked to outcomes such as active travel of children to-and-from their school, after-school venues and activities, vacation/leisure destinations, or junk food shops (Clark et al., 2015; Ikeda et al., 2018; Sadler & Gilliland, 2015).

Exposure can be defined as situations involving a direct encounter or contact with certain types of spaces, and is operationalized in terms of time within, in close proximity of, or views of such spaces. When children's health researchers examine exposure factors, locational technologies such as Global Positioning System (GPS) loggers and geo-tagged smartphone apps are frequently employed and given to research participants (Gilliland et al., 2015; Gong et al., 2014). Passive GPS logging and/or smartphone app logging of children provides spatiotemporal contexts, improves the precision of what constitutes children's environments, and can be contrasted with accessibility of features within buffer distances (DuBreck et al. 2018; Gilliland et al., 2012; Pratt et al., 2004). Research that utilizes location-logging devices and the acquired spatiotemporal data focusses on outcomes such as children navigating their school environments or transportation mapping (Burgess et al., 2016; Clevenger et al., 2019; Villa-González et al., 2018). Researchers have contrasted buffers employed to measure accessibility with exposure data acquired from location-logging devices (Loebach & Gilliland, 2016; Schieman, 2018; Timperio et al., 2015; Sadler & Gilliland, 2015).

Incorporating data on the physical, cognitive, mental, or social health of study participants with exposure data creates a richer dataset that helps to better exemplify the role the environment plays on children's health and well-being. For instance, in addition to carrying a GPS logger or smartphone app, participants may be asked to carry a health-measuring device such as an accelerometer, pedometer, or heart-rate monitor (Kestens et al., 2016a; Villa-González et al., 2018; Wilk et al. ,2018). Alternatively, they may be asked to complete repeated-measure checks after exposure to specific land uses. Such checks have included biomedical measurements, physical aptitude tests, ecological momentary assessments (EMA), activity diaries, or participatory mapping exercises (Chaix, 2018; Loveday et al., 2015; Shmool et al., 2018). This extra layer of empirical data defines *engagement*: exposure plus additional non-spatial measures such as health data, environment data, or locational data. Children that are *engaged* in an activity in a specific land use can have that activity associated with the space *and* with a health outcome.

1.2 Study Rationale and Justification

Despite advancements in portable GPS and other locational technologies used to measure environmental exposures, there still exists a dearth in children's health literature pertaining to accurately measuring how children interact with specific environments during their free time. To address this gap in the literature, this thesis examines children's environmental interactions using data from the Spatiotemporal Environment and Activity Monitoring (STEAM) project, a mixed methods observational research project which collected data on children and the spaces they interact with throughout their daily lives (Details on STEAM provided in section 1.4).

The purpose of this thesis is to examine, using quantitative and spatiotemporal methods, where and how much of their free time children spend within parks and recreation spaces. The practical purpose is to assess the accuracy of location-based methods for delineating the levels of spatial interactions (i.e. potential for exposure and recorded exposures) among children in parks and recreation spaces. These purposes are addressed through the lens of an accessibility, exposure, and engagement framework. "Spatial interactions" in this thesis refers to children's potential for exposure and recorded exposures to parks and recreation spaces of interest.

1.3 Study Area

London, Ontario is a single-tier mid-sized Canadian city with a population of approximately 384,000 (2016 StatsCan census). London is bordered by Middlesex County (2016 population approx. 71,000), which is comprised of large agricultural parcels and interspersed small towns (Robson, 2012). The London urban core is a densely-built area representing historical European settlement (Kossuth, 2005; Robson, 2012). Together, the City of London and Middlesex County contain urban, suburban, and rural built-environment characteristics.

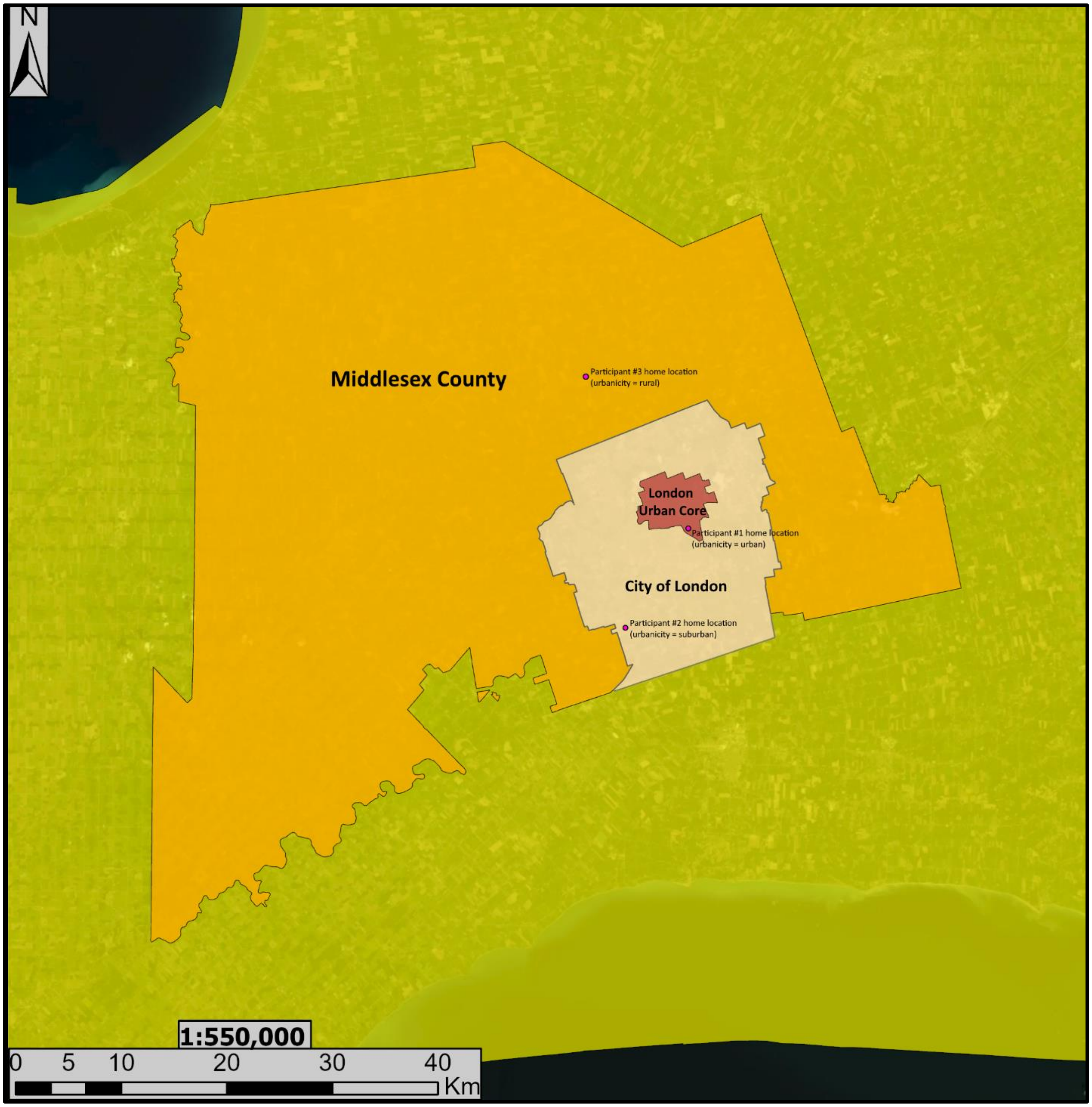

Figure 1.1 – Map of Middlesex-London, displaying the Urban core, Suburban region, and Rural periphery. Labelled are points representing home locations of three hypothetical participants.

1.4 Spatiotemporal Environment and Activity Monitoring (STEAM) Project

This thesis utilizes data from the Spatiotemporal Environment and Activity Monitoring (STEAM) project. STEAM was a three-year (2010-2013) research project conducted throughout southwestern Ontario. The purpose of the STEAM project was to examine the influence of the physical environment on children's (ages 9-14 years) health-related behaviors and environmental interactions (Mitchell, 2016; Richard, 2014). STEAM used mixed methods to collect social, demographic, and locational data from a representative sample of Canadian children living in urban, suburban, small town, and rural locales of southwestern Ontario. A full description of the STEAM methodology is described in Chapter 3 of this thesis. The STEAM data was used to inform methods, practices, and policies aimed at improving the overall health of Canadian children, particularly in the midst of epidemics of obesity and sedentary behavior (Gilliland, 2010). A subsequent STEAM study was conducted in 2016 in the rural municipalities of Nipigon, Dorion, and Red Rock located in northwest Ontario (Button et al., 2020; Schieman, 2018). Refer to chapter 3 for a full breakdown of study protocol, data-collection mechanisms, data processing, and statistical and spatial analysis methods.

Outcomes examined by researchers who previously analyzed STEAM data include access to junk food outlets and junk food purchasing (Sadler & Gilliland, 2015; Sadler et al., 2015), physical activity levels (Mitchell, 2016; Schieman, 2018; Button, 2020), active travel (Rivet, 2015), mental health and well-being (Tillmann, 2017), and perceptions of the social and built environment (Loebach & Gilliland, 2016; Button et al., 2020).

1.4.1 STEAM and the Socio-Ecological model

The Socio-Ecological model (SEM), made popular by Bronfenbrenner (Eriksson et al., 2018), is frequently applied in STEAM research. Due to its flexibility in delineating independent variables from multiple levels of societal interactions, the SEM is well suited to encompass the spatial and social phenomena involved when children interact with their environments (Mehtälä et al., 2014). This thesis draws from the SEM developed by Bronfenbrenner (Eriksson et al., 2018) and categorizes socioeconomic, demographic, social, and built environment data acquired from STEAM into each SEM level. Figure 1.2 below shows an example of a modified SEM that includes variables acquired from STEAM's GPS, GIS, and survey data-collection mechanisms.

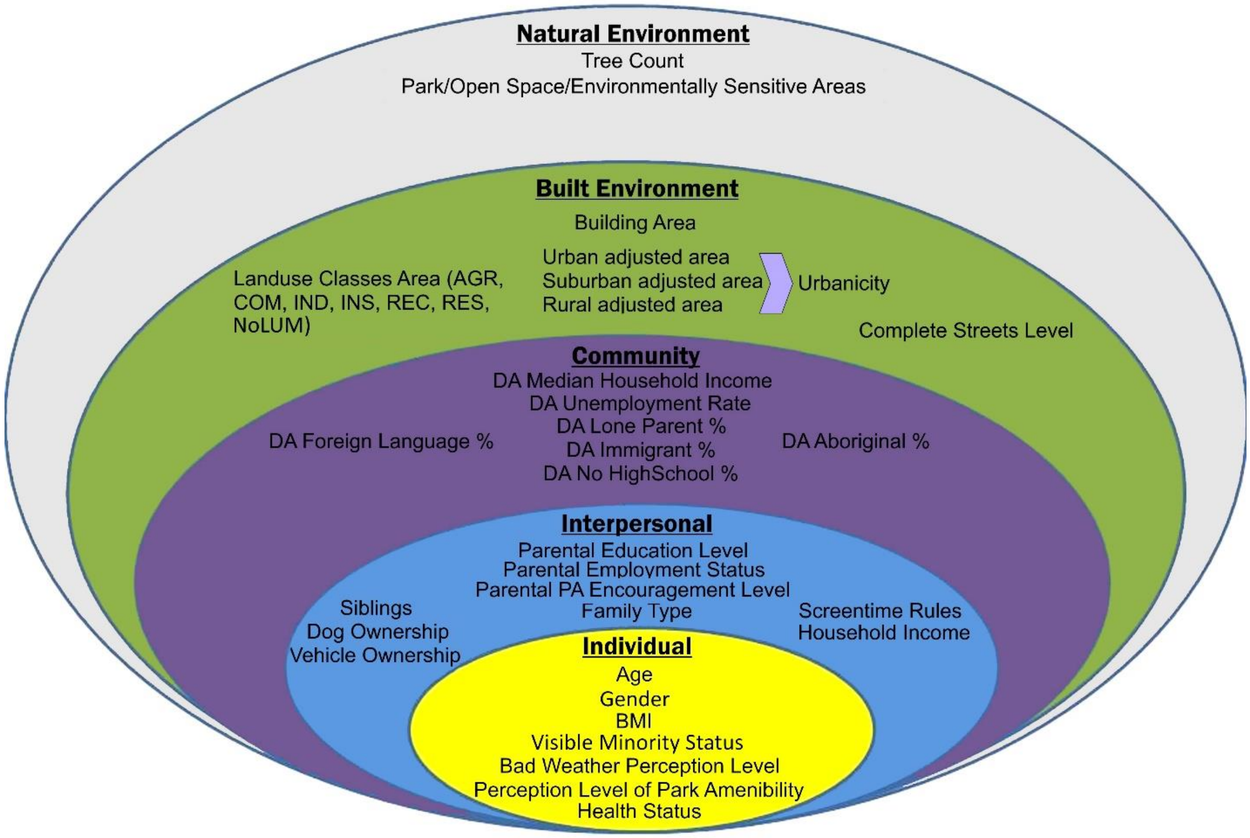

Figure 1.2 – Example Socio-Ecological model (SEM) including variables used in exploratory analysis to uncover associations in children's proportions of free time in parks and recreation spaces

1.4.2 STEAM in other scholarly works

Publications or theses that have analyzed STEAM data derived their measures in different ways to relate children's locations to health or exposure outcomes. For instance, in her 2018 MSc thesis, Schieman examined the levels of spatial interactions of children in rural northwest Ontario through the lens of a spatial typology incorporating green, blue, urban, and rural spaces. Schieman segmented these levels of spatial interactions into the space types, then linked them to time-weighted intensity of exposure, and further examined the data through a weekday/weekend split. Mitchell, in her 2016 MA thesis, explored how physical activity levels can vary by home-neighbourhood size and by participant gender, and how variations in physical activity levels fluctuate as neighbourhood characteristics fluctuate.

Through a lens of children's independent mobility, Loebach (2013) examined STEAM children's perceptions of their environmental ranges via qualitative (focus groups) and spatiotemporal (GPS and GIS) methods. Tillmann's 2018 MSc thesis combined quantitative and qualitative data acquired from STEAM to uncover associations between SEM factors of children, their level of greenspace interactions, and their mental health and well-being.

Similar to aspects of this thesis, Rivet (2016) employed a spatially contiguous hexagon dataset that covered the STEAM study area. The hexagon dataset Rivet employed aided in discovering physical environment characteristics that were statistically significant factors of children actively travelling to school. Also exploring active travel, Richard (2014) applied STEAM participant GPS logs to delineate routes to school, then combined the routes with physical activity measures and home location coordinates. This combination of data allowed Richard to uncover the impacts of active travel on children's overall physical health. Relating more to the accuracy and precision of GPS logger data, Healy, for his 2019 PhD dissertation, developed a processing model that utilized the inherent geometric properties of GPS loggers to determine whether children carrying them were indoors or outdoors.

Nonetheless, research using STEAM has not investigated the complexity of differences when measuring children's levels of interaction in parks and recreation spaces, nor has there been research that uncovers which socioecological attributes of children influence the frequency and duration of interaction in parks and recreation spaces.

1.5 Research Questions

The overarching goal of this thesis is to examine where and how much of their free time children of different characteristics spend within parks and recreation spaces, and to examine how certain location-based methods differ in terms of accurately measuring children in such spaces. In order to achieve this goal, this thesis will attempt to answer four research questions. As outlined in section 1.2, a goal of this thesis is to examine how different ways of measuring children's levels of spatiotemporal interactions within parks and recreation spaces can lead to different results. For example, one particular difference is between an applied policy within an urban-suburban setting – specifically one involving parks and recreation spaces frequently used by children – and how the policy matches with measured use of those spaces. To achieve the overarching goal, this thesis intends to answer these four research questions:

Research question #1 is "*How accessible are parks and recreation spaces to children?*". This question will focus on what "accessibility" truly means by analyzing different ways to measure accessibility from participant home locations to an array of parks and recreation types. This question also relates to an applied policy, in that answers will address specific spatial aspects of the City of London's parks and recreation master plan (City of London, 2019).

Research question #2 is "*What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?*" This question will determine the percentage of participants exposed to fifteen distinct types of parks and recreation amenities throughout Middlesex-London, and will dichotomize such spatial exposures by day type. Free time is defined as time outside of structured hours, which is essentially after-school hours up to bedtime (11p.m. EST), and all waking hours on weekends and holidays.

Research question #3 is "*How much free time do children spend in parks and recreation spaces on (a) weekdays and (b) weekends?*". Examining this question via STEAM data will reveal how much time (i.e. magnitude of exposure) outside of structured hours children are spending within parks and recreation spaces. For instance, a low proportion of free time spent by children in parks and recreation spaces may be indicative of either disinterest with those spaces or lack of time, regardless of how accessible they might be from home locations.

Combined, the first three research questions provide a foundation for which research question #4 can build upon. Research question #4 is "*What are the individual, interpersonal, and built environment factors associated with free time spent on (a) weekdays and (b) weekends in parks and recreation spaces?*". This question drills down into characteristics of STEAM participants who interact with parks and recreation spaces. The question uncovers how certain attributes of children (e.g., age, gender, ethnicity) may be more related than others to the magnitude of exposure to parks and recreation spaces. These attributes are important to know, as determining which subsets of children spend less time in parks and recreation – thus less time potentially improving their health – could aid policymakers in crafting promotions and programs aimed at equitable exposure to parks and recreation spaces.

1.6 Thesis Format and Chapter Descriptions

This thesis is presented in a monograph style. Monograph was chosen as it is well suited to telling a complete story of the research conducted. This is especially important because the STEAM project and the spatial analyses involved require a detailed methodological breakdown. The chapters included in the monograph are as follows:

Chapter 2 is a literature review into research that measures children's spatial interactions, particularly within parks and recreation spaces, and how health outcomes are associated with levels of interaction. The chapter examines how "spaces" can be defined and grouped, and how "children" can be defined and grouped in a demographic and socioeconomic sense. A rapid systematic review of studies and articles utilizing passive GPS logging of children, and relating their locations to spatial interactions, is included.

Chapter 3 details the methods of data collection used in the STEAM project and the processing of locational and spatial data. The chapter outlines how this thesis measures accessibility of parks and recreation spaces from home locations versus actual exposure and engagement to parks and recreation spaces, based on type of day (weekdays or weekend days). The measures applied to answer each of the four research questions, and the technologies applied to process and analyze STEAM data, are detailed in full.

Chapter 4 provides results of the analysis undertaken to answer the four research questions, including descriptive statistics of the study population, inferential statistics of the SEM groups related to proportion of free time in parks and recreation spaces, and statistical differences regarding buffer distances that relate to accessibility/exposure/engagement of children to those spaces. These results are provided in seventeen tables that highlight statistically significant findings for each research question.

Chapter 5 provides in-depth discussion of the key findings pertaining to all four research questions. In particular, the chapter provides interpretation of the statistical relationships uncovered amongst key independent variables, such as age, gender, visible minority status, household income, parental education, urbanicity, and distances to nearest parks and recreation spaces. The chapter also includes discussion on the differences between the City of London's parks and recreation master plan service areas, and STEAM participant exposures to the recreation types the service areas apply to. Furthermore, the chapter considers how parks and recreation policies could be modified to be more accessible for all children, thus providing a more equitable parks and recreation landscape. Additionally, limitations of STEAM and the specific research in this thesis are described. The chapter concludes with a look into future research opportunities, such as examining other aspects of policies involving parks and recreation spaces, methodological and research-design enhancements, and interventions aimed at increasing children’s proportion of free time in parks and recreation.

2 Literature Review

Providing a foundation for this thesis, this chapter will delve into the scholarly literature involving children's health, spaces children interact with, and the analytical approaches researchers use to investigate them. The first major part will discuss the ways research on children's geographies records and measures children's spatial interactions. The second major part will discuss how social and demographic aspects of children and their living situations have been associated with the spaces they interact with.

A framework for measuring levels of spatial interactions will be used to focus the review, as will the Socio-Ecological model and how each level of the model addresses independent variables common for children in health geography research. The third major part is a rapid review of studies and articles published from 2000 – 2019 that investigate associations between children's health outcomes and/or their spatial interactions by utilizing GPS and/or GIS. Altogether, this chapter comprises a thorough literature review that provides the foundation and justification for this thesis and its four research questions.

2.1 Children's Health and Spatial Interactions

Over the last few decades, Canadian children's physical, social, and mental health has declined. Most notably, rates of adiposity have increased, as have rates of sedentary behavior (Brennan et al., 2014; Prince et al., 2020). In successive years of its annual report, ParticipACTION has noted Canadian children are increasingly physically inactive, increasingly remaining indoors, and increasing their screen time (C. F. Canada, 2020; ParticipACTION, 2020). These reports emphasize the need for children to get outdoors, get active, and reap the health benefits associated with doing both. Positive health outcomes among children have been associated with outdoor activities, such as increases in cognitive and mental health due to greenspace exposure (Remmers et al., 2019; Tillmann et al., 2018; Wu et al., 2014) or moderate-vigorous physical activity (Jones et al., 2009; Mitchell et al., 2016; Ward et al., 2016), increases in social connectedness (Wood et al., 2013; Wray et al., 2020), and improved knowledge of the natural world (McCree et al., 2018; O'Brien, 2009).

Due to these trends in children's health, coupled with the ineffectiveness of clinical settings in reversing unfavorable health outcomes among children (Felver et al., 2017; Smith & Bradshaw, 2017), health researchers are increasingly focused on *where* their investigations and interventions are located. Clinical settings are no longer seen as the *de-facto* setting for where positive health outcomes can be attained for children (Smith & Bradshaw, 2017; Wells et al., 2014). Rather, it is increasingly evident influences of the environment on children's lives play a huge part in shaping both children's measurable health outcomes and activities that potentially improve them. Scholars have noted that activities and venues children are frequently exposed to, engaged in, and become fond of will shape the activities and venues they are exposed to and engaged in during their adult years (Collins et al., 2012; Fitch et al., 2018). Environmental influences related to children's health outcomes during their free time (e.g. after school, weekends or holidays) are frequently associated with interactions in parks and recreation spaces (Alexander et al., 2013; Chaudhury et al., 2019; Dunton et al., 2014; Mitchell et al., 2016; Van Hecke et al., 2018; Veitch et al., 2012). By utilizing readily-accessible amenities requiring minimal training, it is in parks and recreation spaces where children can realize improvements in health-related outcomes.

Nevertheless, in tandem with the aforementioned health declines, researchers have also uncovered a decline in the frequency, duration, and physical engagement of children within parks and recreation spaces (ParticipACTION, 2020; Prince et al., 2020; Toftager et al., 2014). Bejarano et al. (2019) found that both increased sedentary behavior and screen time was associated with a significant decrease in exposure to parks and recreation spaces and the activities therein that engage children toward better overall health. Indeed, sport participation rates among children have been steadily declining, particularly for field sports played outdoors (Button, 2020; McGrath et al., 2015). This thesis examines spaces that foster participation in sports among children, but more broadly, this thesis examines how approaches to measuring health-positive spaces associated with children and the levels of interaction they have in those spaces are best measured.

2.2 Measuring Children's Spatial Interactions

Whereas the need to gauge children's frequented, habitual, and occasional spaces has been emphasized (Loebach & Gilliland, 2016; Moore, 1986), how to best measure levels of interactions with those spaces has not been emphasized as much by children's geography researchers. Compared to clinical approaches to address children's sedentary behavior and the associated adverse health outcomes, evaluating children's spatiotemporal associations with parks and recreation spaces is nascent.

Throughout the twentieth century, mandates and policies that developed and managed parks and recreation spaces for children were largely technocratic, approached clinically and with little input from the people being served by the spaces (Parks Canada, 1994; Pacchi, 2018). Little attention was paid to the health benefits that parks and recreation spaces can foster throughout childhood, and how provisioning quality and accessible spaces can influence a child's perceptions of them, perceptions that endure throughout their lives (Chaudhury et al., 2019; Collins et al., 2012; Veitch et al., 2016). Across Canada, urban-suburban parks and recreation spaces are managed by municipal and regional authorities, many of which have dedicated divisions overseeing budgeting and development/maintenance of the spaces. Oversight of parks and recreation spaces has, over recent years, incorporated public feedback, site-selection analyses, contract-bidding processes, and collaboration with NGOs (Greer et al., 2015; Putnam, 2000; Thompson et al., 2014; Wray et al., 2020).

However, management still involves touch-and-go processes which lack theoretical or quantitative backing from empirical research. Identifying and acknowledging that lack of empirical backing, health geographers increasingly undertake research projects aimed to objectively measure health-influencing environments and people's interactions with them. Since 2000, when intentional degradation of GPS signals was removed by the US government, location-enabled tools such as GPS have been increasingly employed to objectively measure children's spatial interactions (Krenn et al., 2011). Amidst numerous observational studies, GPS loggers or geotagged smartphones have been used to measure children's locations with increased spatiotemporal precision (Loveday et al., 2015; McCrorie et al., 2014; Yue et al., 2014). Additionally, and often in synchronicity with location-enabled tools, accelerometers, pedometers, heart-rate monitors, and ecological momentary assessment (EMA) apps have been used to measure children's health outcomes (Boettner et al., 2019; Collins et al., 2012; Mitchell et al., 2016).

Regardless of the rapid development of location-enabled methods, and their applicability to mandates and policies surrounding parks and recreation spaces, researchers often still employ methods that lack accuracy and/or spatial contextual depth. Indeed, many public health researchers, intending to objectively gauge locations children are exposed to, rely on expedient proximity-based methods that are not ground-truthed with their research participants' concrete exposures (Kwan et al., 2018; Sadler & Gilliland, 2015; Wang et al., 2018).

2.2.1 Accessibility and Proximity

Frequently, researchers have used buffers – predefined areas surrounding locations and paths common to participants' lives and travel patterns – to gauge the accessibility of children to parks and recreation spaces. Often, researchers employ only simple Euclidean buffers rather than buffers surrounding multiuse pathways or circulation networks (i.e. road networks combined with multiuse pathways) which more thoroughly align with the route options children must take to reach destinations (Browning & Rigolon, 2019; Crouse et al., 2017; Kestens et al., 2018). Home and school locations are often used as the origin for buffers, with various buffer distances generated and the *potential* for spatial interactions subsequently measured (Kwan et al., 2018; Sadler & Gilliland, 2015; Wang et al., 2018). Yet without data garnered from location-enabled tools or other data-collection mechanisms coupled to them, buffers remain a mere potential for exposure to parks and recreation spaces, not confirmed exposure nor exposure with any intent.

Children navigating local environments are subject to barriers and pressures, most notably from parents/guardians, other authority figures, and from restrictions imposed within the spaces themselves (Botha & Kourkoutas, 2016; Siu, 2013; Taylor et al., 2018). Researchers often incorporate these barriers from GIS data, but confirm them with GPS tracks, activity diaries, or surveys. This confirmation of barriers clarifies the complete picture of children's navigation of their local environments. Buffers alone cannot provide such clarification, nor can simple Euclidean buffers accurately measure the complexities of navigation children undertake to reach health-positive environments (Kwan et al., 2018; Sadler & Gilliland, 2015).

To address this shortcoming with Euclidean buffers, some children's geography researchers have upgraded their buffering methods by utilizing street-path network datasets of their study areas. These network datasets, often called circulation networks, comprise the roads, sidewalks, trails, and shortcuts available to child participants. Circulation networks involve extensive network analysis by GIS technicians, wherein they define nodes, barriers, cut-throughs, and speeds of various segments (Apparicio et al., 2017; Gilliland et al., 2012). Depending on the robustness of technical work put into a circulation network dataset, there is a measurable degree of improvement over Euclidean buffers, not to mention a practical advantage. For instance, a Euclidean buffer may denote a park near a child's home is accessible within a 500m radius, yet the circulation network shows the park is behind the fenced yards of detached homes, and actually requires the child take a circuitous route. This measurement incongruity can be seen with other spatial types and land uses: routes to school being misrepresented due to busy intersections not being factored in, trip chaining to multiple destinations by vehicle not being factored in, and regulations regarding permitted people and times for spaces not being factored in (Kestens et al., 2016b; Putnam, 2000; Wilson et al., 2018).

Accessibility is only one step in understanding the full picture of children's spatial interactions. Essentially, a buffer-only spatial analysis, even one incorporating a complex circulation network, can leave out critical data about participants and the locations they are objectively exposed to. That lack of both context and precise measurement of actual exposure has not stopped researchers from continuing to use simple yet impractical buffers for subsequent estimation of health outcomes (Kwan et al., 2018; Sadler & Gilliland, 2015).

2.2.2 Exposure to Spatial Types

As discussed, using simple accessibility measurements as indicative of spaces that influence children's health outcomes is subject to inaccuracies and spurious associations. To improve on simple accessibility measures, some researchers additionally incorporate exposure measurements. These exposure measurements are often seen in observational or natural experiments that recruit child volunteers, wherein the volunteers are given a location-enabled device to carry throughout their waking hours (Chaix, 2018; Kerr et al., 2011; Krenn et al., 2016). Devices often given to child volunteers include GPS loggers or a location-enabled app for their smartphone (Gong et al., 2014; Loveday et al., 2015; McCrorie et al., 2014; McCullough et al., 2018). Participants carrying such devices and following an observation protocol has provided children's health geographers with invaluable location data useful for associating spaces to health outcomes at the individual level. Observational studies utilizing location data provide their models an objective basis for delineating (e.g. activity spaces, environment classifications) and weighting (e.g. time-stamped durations, proportions) spatial interactions.

Defining spaces children interact with is critical when incorporating exposure data from location-enabled devices. Theoretical definitions of spaces are used by researchers to gauge the levels of influence environments have on children's health outcomes. For instance, Loebach & Gilliland (2016), expanding on Moore's work on spatiotemporal contexts (Moore, 1986), defined her participant children's spaces as frequent, habitual, or occasional. Putnam (2000) has defined spaces as SLOTH – Sleep, Leisure, Occupation, Transportation, Home – and tailored it for children by suggesting Sleep can include multiple residences (e.g. sleepover at friends or grandparents, custodial parent's home) and Occupation is predominantly school. Hagerstrand's time-space paths to common destinations has also been used by researchers, particularly those who have participants perform participatory mapping exercises (Arunkumar et al., 2018; Shmool et al., 2018). Another common distinction made in spatial types is the broad urban-suburban-rural classification scheme. Whichever of those types they use, children's health geographers often modify definitions of urban-suburban-rural, adjusting them to local conditions and population complexities. For instance, McCormack & Meendering (2016) used an urban-rural divide for their research into children's activity levels, while Button et al. (2020) used a small-town versus rural-remote classification scheme to align with their study area.

Upon a spatial classification scheme being chosen and data collected from location-enabled devices carried by participants, linking the two frequently occurs via GIS. Through the implementation of spatial objects, GPS coordinates can be operationalized as points on a map, and then those points can be intersected with defined regions. Intersecting the points with regions has been accomplished using tessellated surfaces comprised of equal-sized spatial objects (Healy & Gilliland, 2012; Wang & Kwan, 2018), using raster surfaces from density measurements of points (Kestens et al., 2016a; Thierry et al., 2013), or using predefined spatial objects of census/electoral divisions such as dissemination areas, census tracts, or wards (Tucker et al., 2009). Ideally, researchers tailor the classification scheme they use to spaces that have been known to influence health outcomes they are evaluating.

Recent flexible approaches, such as fine-resolution spatial bins, have allowed researchers to readily aggregate data into spatiotemporal contexts that better fit their research questions, or to discover what the contextual spatial influences actually are via hotspot, space-time-cube, and clustering analyses (Fritz et al., 2013; Kang et al., 2018; Kwan et al., 2015). Nevertheless, even with all the capabilities of GPS and GIS factored into research design, mere exposure to spatial types is not necessarily indicative of children engaging in activities that promote positive health outcomes.

2.2.3 Engagement within Spatial Types

Research that expands on exposure (locations plus spatial classification) has involved the addition of frequencies/durations of health-related or time-related variables. Enriching exposure by means of validated measures of health or by means of validated measures of time spent in spaces has been referred to as engagement (Schieman, 2018; Tillmann et al., 2018). Pertaining to measurements located in spaces related to the physical health of participants, devices such as accelerometers, pedometers, and heart-rate monitors have been provided to participants alongside location-enabled devices (Boettner et al., 2019; Collins et al., 2012; Mitchell et al., 2016). Measurements related to mental health of participants have involved EMA apps or sound recording devices designed to collect data on the experiences and opinions of participants; such data subsequently informs themes used in qualitative analysis (Boettner et al., 2019; Bürgi et al., 2016; Chaix, 2018).

Weighting spatial bins (e.g. fishnet or hexagonal) by time duration or frequency of intersections is another approach seen in children's health geography research (Healy & Gilliland, 2012; Wang & Kwan, 2018). For example, Schieman (2018), using ArcGIS, created a contiguous hexagonal bin surface of their area of study and weighted each bin by the cumulative amount of time – as determined by GPS loggers they carried – participants were exposed to them. Engagement within spatial bins has been further enhanced by incorporating qualitative data from children into the GIS spatial objects, though doing so may introduce perceptual and recall biases (Boettner et al., 2019; Wang et al., 2018).

Additionally, understanding the limitations of location-enabled technologies used in observational studies is key to avoiding underestimating or overestimating duration or frequency of engagement in spaces. For instance, loss of GPS signal inside buildings can inflate proportion of exposure or engagement in favor of outdoor spaces. When synchronization with health-related measurement devices, improper syncing can lead to flawed statistical analyses of relationships

(Clevenger et al., 2019; McCullough et al., 2018). Kwan et al. (2018) stated that relating health outcomes to spatial interactions can be spurious if both the health measure and the level of spatial interaction do not logically and temporally match. For example, relating amount of engagement in a neighbourhood greenspace to cognitive health scores is not feasible unless done over numerous time series *and* controlling for other influences (Ward et al., 2016). Such methodological conundrums make engagement a less utilized approach of relating types of spaces to influences on children's health outcomes.

2.3 Associating Attributes of Children to Types of Spaces

Given previous discussion on how children's spatial interactions have been measured by researchers, it is apropos to discuss the thoroughness and accuracy of how the two main elements, children and spaces, have been applied by researchers. It is imperative for researchers to properly define and analyze aspects of children, properly define and analyze aspects of spaces, and understand the myriad complexities of both. Have researchers fully examined the social and built environments children interact with? Have researchers utilized land use categories that can reasonably link research outcomes to various characteristics of children?

Environments frequented by children have been defined using land use classifications, spatial typologies, census divisions, and satellite imagery raster surfaces (Apparicio et al., 2017; Healy, 2018; Kwan, 2012a; Sandercock et al., 2010). Environments have also been defined by frequency of use, duration of use, themes, physical barriers, social barriers, and quality rankings (Taylor et al., 2018; Van Hecke et al., 2016; Woodland, 2008). Each of these has their complications, ranging from perceptual and recall biases to the modifiable areal unit problem (Boettner et al., 2019; Wang et al., 2018).

When it comes to quantifying environments via GIS or other object-oriented applications, researchers have incorporated variable data within the spatial objects that define their spatial typology (Drewnowski et al., 2019; Mitchell et al., 2016; Schieman, 2018b; Wang & Kwan, 2018). Environments have also been quantified at different scales of space and time, with hard or soft boundaries, or with demarcations of the built environment (urbanicity, path connectivity, land use mix). These quantification and demarcation methods have, in many cases, reduced the

Uncertain Geographic Context Problem (UGCoP) described by Mei-Po Kwan (Kwan, 2012b, pp. 959). UGCoP, as described by Kwan, denotes that "…*findings about the effects of area-based contextual variables on individual behaviors or outcomes may be affected by how contextual units (e.g., neighbourhoods, census division, land use classes) are geographically delineated and the extent to which these areal units deviate from the true geographic context.*" Flexibility in spatial delineations, such as the ability to aggregate a set of fine-resolution, contiguous spatial objects based on variable values, helps to reveal the complexity of influences on children's health outcomes. By avoiding static boundaries, this flexibility works to dampen UGCoP.

2.3.1 The Socio-Ecological Model (SEM) and Children

Expounded upon in chapter 1, the Socio-Ecological model is well suited to encompass the spatial and social phenomena involved in children interacting with their environments (Mehtälä et al., 2014). The levels of the SEM can be adjusted to incorporate independent variables that thoroughly encompass measurable aspects of a child participant. These variables can be logically placed within the level of social interaction where influence on outcome(s) is greatest. Researchers may also define a set of variables that are encompassed within an overall concept, e.g. number of siblings and peer pressure encompassed in peer support for certain activities/behaviours. Researchers may place them at different levels of the SEM to see what, statistically speaking, their level of influence is. Another example would be a child participant's perception of support for engagement in parks and recreation spaces, where the perception is an individual-level variable yet may also relate to sibling support (interpersonal-level variable) or the support the built environment provides (built-environment-level variable).

Using the SEM has allowed children's health geographers and public health researchers to conceptualize the environments influencing children's activities by acknowledging multifactorial complexities (Eriksson et al., 2018; Mehtälä et al., 2014; Townsend & Foster, 2013). At the individual level of the SEM (also referred to as intrapersonal level), personal demographic characteristics have been shown to be associated with accessibility, exposure, and engagement (AEE) to parks and recreation spaces (Marquet et al., 2019; Mitchell et al., 2016). Some researchers have stated how modifying parks and recreation spaces to improve health-related outcomes for people having specific individual level variable attributes is the most difficult to execute and measure (Greer et al., 2015; Van Hecke et al., 2018). The interpersonal level of the

SEM includes family and household socioeconomic characteristics, which have been associated with AEE for parks and recreation spaces (Chaudhury et al., 2019; Dunton et al., 2014). For instance, in their systematic review, Van Hecke et al. (2018) found among eligible studies that the number of siblings a child has is significantly related to their exposure and engagement in recreation spaces near their home. Adjusting parks and recreation spaces to accommodate different attributes of interpersonal level variables involves promoting inclusivity and providing an array of amenities (Botha & Kourkoutas, 2016; ParticipACTION, 2020).

SEM complexity increases as it reaches the third level, the social environment (also referred to as community level). At this level, characteristics of neighbourhood spaces and institutions common amongst children (e.g. schools, community centres, shops, pocket parks) plus census data at neighbourhood scales (e.g. Dissemination Areas, Forward Sortation Areas, Wards) are typically added into the SEM. Sensitivity of the spatial context increases at the social environment level, as influences of the various spaces increase or decrease based on their demarcation (Bürgi et al., 2016; Kwan et al., 2018). Adjusting parks and recreation spaces to accommodate different attributes of social-environment-level variables, many of which are influenced by interpersonal and individual level variables, involves an interplay with municipal planners, property developers, and interest groups (Greer et al., 2015; Putnam, 2000; Thompson et al., 2014). The built-environment level includes the configuration of the human landscape, both broadly (urban-suburban-rural) and specifically (circulation network patterns, distances to nearest spaces of interest). It is at this highest level of the SEM that modifications to parks and recreation spaces are evaluated amidst their interrelations to other types of spaces, such as residential, commercial, or institutional spaces (Thompson et al., 2014; Wilk et al., 2018; Williams et al., 2018).

Altogether, conceptually situating the variables that encompass a child, along with conceptually situating their spatial interactions, can be effectively achieved via the Socio-Ecological model. The environmental levels of the SEM – social and built – can be contextualized by research participants adding individual and interpersonal level data from data-collection mechanisms like daily diaries, surveys, questionnaires, EMA, focus groups, and participatory mapping exercises. Researchers have noted numerous drawbacks from acquiring contextual data, such as recall bias, peer pressure, self-selection bias, and disparate power relationships between children and interviewers (Button, 2020; Li & Sullivan, 2016; Wang et al., 2018; Wilk et al., 2018). However, numerous tools have been developed by researchers, for example credibility-transferability-dependability-confirmability, Pediatric Quality-of-Life, Strengths-Difficulties Questionnaire, that can validate perceptual data acquired from participants (Amoly et al., 2015; Button, 2020; Varni et al., 2005).

Frameworks that encompass proximity, activity, and movement of participants to and from spatial types such as parks and recreation spaces have been implemented in numerous studies involving children's health geographies. The framework of accessibility, exposure, engagement (AEE), frequently employed by researchers in the Human Environments Analysis Laboratory (https://theheal.ca/) is ideally suited to examine aspects of children, the spaces they interact with, and the continuing evolution of both. It is within the AEE framework that this thesis will examine the ways children and their levels of interaction with health-promoting parks and recreation spaces can be accurately measured.

2.4 Rapid Review: Synthesis of Literature via PICOTS

To assess the scholarly literature related to aspects of children and their spatial interactions, a rapid review was conducted. The review utilized the Population, Intervention, Comparison, Outcome, Time, Setting (PICOTS) method for identifying journal articles on studies related to children, spatial interactions, and associations with improving health outcomes.

2.4.1 Study Eligibility

A PICOTS framework for searching and identifying relevant articles amongst research databases was utilized in this rapid review. PICOTS provides a consistent, itemized framework for developing researchable questions (Abbade et al., 2016). The eligibility criteria for articles was as follows:

Population: Children ages 5-18 years (i.e. school-aged children).

Intervention: Any observational, cross-sectional, longitudinal cohort, or controlled-trial study utilizing passive-GPS logging.

Comparison: Randomization or control groups not required.

Outcome:	Any physical, cognitive, or mental health outcomes being related to any types of spaces.
Time**:**	Published between May 2000 and December 2019.
Setting:	Studies conducted in Australia, New Zealand, Japan, North America, Latin America, or Europe.

In addition to the above requirements for eligibility, only quantitative studies that provided inferential results were included; purely qualitative studies were excluded. Due to several existing rapid reviews on studies linking locational data to diet, any studies with solely dietary outcomes were excluded from consideration. Eligible languages were English or Spanish.

2.4.2 Database Search Procedure

With the aid of a research librarian, eight research databases were chosen that were geared towards the range of PICOTS elements: Cochrane Library, EMBASE, GeoRef, PubMed, PsycINFO, Scopus, SPORTDiscus, and Web of Science. On December 1, 2018, these databases were searched and results compiled, with an updated search performed on December 11, 2019. Additionally, eighteen journals were identified and hand-searched for publications fitting the PICOTS criteria; see Appendix A for full list of hand-searched journals. Database search terms are presented in Table 2.1.

Table 2.1 – Search terms applied in eight research databases

Population	child* OR youth* OR teen* OR adolescen* OR schoolchild* OR "school children"
AND (independent var)	GPS* OR "Global Positioning System" OR track* OR "location tracking" OR satellite
AND (outcomes)	"travel mode" OR "active travel" OR "physical activity" OR MVPA OR TDPA OR SB OR sedent* OR inactiv* OR mode OR walk* OR bicycl* OR driv* OR car OR truck OR bus* OR vehic* OR transp* OR transit OR multimod* OR multi-mod* OR health* OR sleep* OR "sleep duration" OR "sleep quality" OR "mental health" OR stress OR well-being OR emotion* OR anxiety OR anxious OR mood OR "mood disorder" OR ADD OR ADHD OR "attention deficit disorder" OR depression OR "depressive symptoms" OR "psychological distress" OR resiliency OR self-

	esteem OR self-confidence OR cogn* OR space* OR spat* OR “land use” OR “land use class” OR “land use category”
NOT (exceptions)	“general practitioner” OR “general practitioners”

Due to their synonymity with children’s activity locations/spaces (Schoeppe et al., 2016), travel and mobility terms were included. Due to the term often being abbreviated as ‘GPs’, which conflicts with Global Positioning System’s abbreviation ‘GPS’, the term “general practitioner” was explicitly excluded in title searches. Due to GPS studies’ wide range of publications across interdisciplinary and discipline-specific journals, the review focused on sensitivity over specificity. Over ninety thousand search results were exported into Mendeley. Three reviewers screened titles using the PICOTS criteria and a retention mentality (i.e. if unsure, keep article for later phases of screening). Once title screening was completed, duplicates were removed. To numerically keep track of screening results, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was applied. The PRISMA diagram in Figure 2.1 outlines the reduction of search results from the original ninety thousand plus. Altogether, 49 studies that fully met PICOTS eligibility criteria were included in the rapid review.

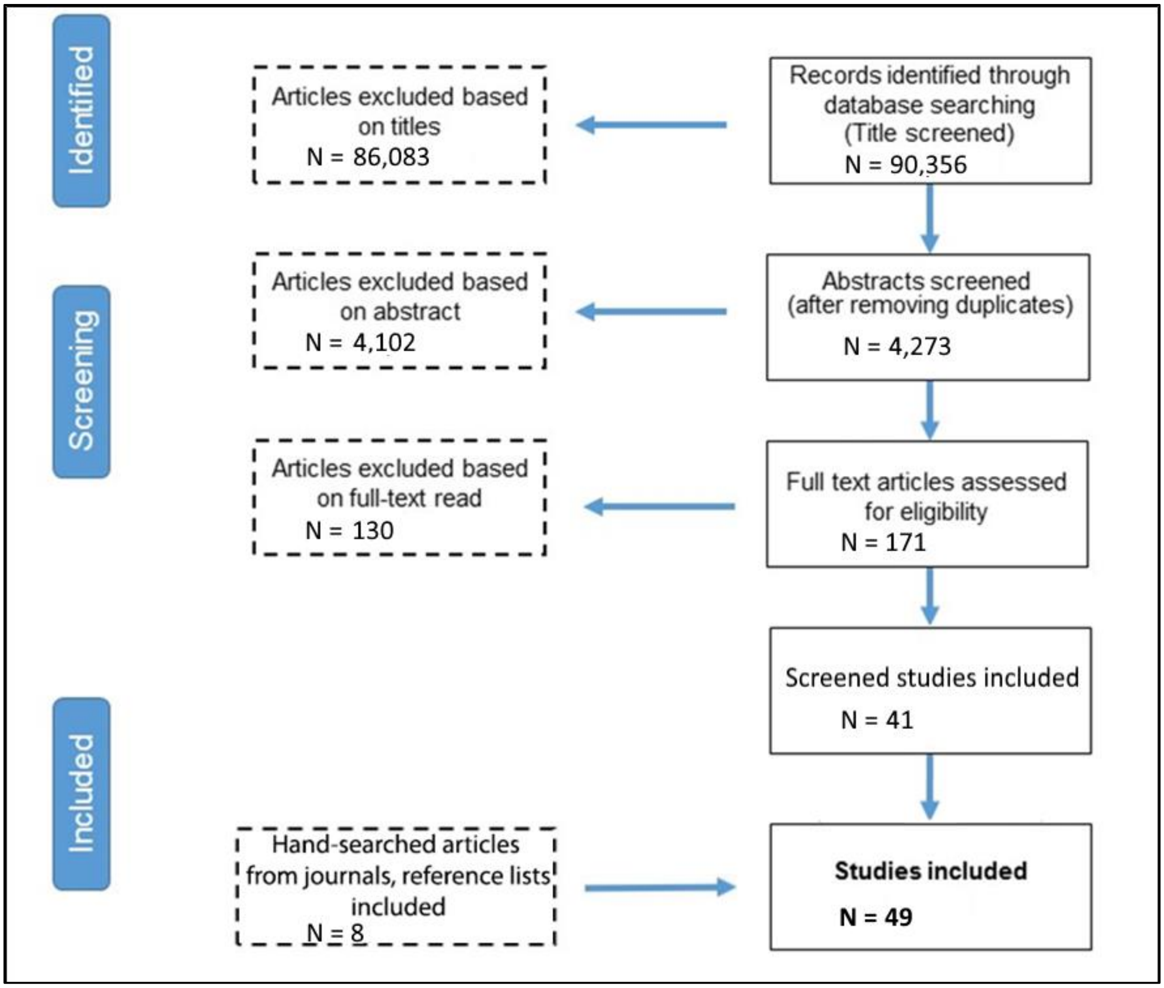

Figure 2.1 – PRISMA diagram of screening process of articles for inclusion into rapid review

2.4.3 Data Extraction and Categorization

To aid in review synthesis, an Excel table was developed to record study characteristics of eligible articles. Thirty study characteristics were recorded and subcategorized into sections as follows:

General:	Publication information, data-collection periods, sample sizes, study design, measured health outcomes.
Demographic:	Ages of participants, genders of participants, ethnicities of participants, languages of participants, school type.
Socioeconomic:	Household income, household composition, parental education, parental employment.

Geographic: Location of study, distances measured, climate/weather measured, spatial typologies used.

GPS Technology: Recording interval (epoch), GPS geometric variables analyzed, health-measuring devices used/synchronized, analysis tools.

Children's exposure to and engagement with land use categories of their local environments can be influenced by attributes of weather, particularly heavy precipitation, gusting winds, and extreme temperatures (Herrador-Colmenero et al., 2018; Remmers et al., 2019; Tucker & Gilliland, 2007). Given this, the review assessed whether seasonality or weather was accounted for in each article.

2.4.4 Quality Assessment of Studies

Due to its synchronicity with the subcategories of this review's study characteristics, and its rigorous examination of study design, the McMaster University Effective Public Health Practice Project (EPHPP) tool was chosen as this review's quality assessment tool (Effective Public Health Practice Project, 1998). As initially developed, the tool was not perfectly suited for GPS-based studies. Therefore, formulated in consultation with international experts experienced in GPS logging research, a section containing five questions assessing the quality of articles' discussion of working with GPS data was added. Refer to Appendix B for the added section and its questions.

Quality ratings of eligible articles were conducted by two researchers, followed by a third arbiter for disagreements; agreement was strong between the two researchers (Cohen's kappa = 0.87). Study quality was rated as Strong, Moderate, or Weak. The researchers understood that due to page/wordcount limitations of journals publishing the eligible articles, elements of discussion may not have been included. To combat this, the two researchers also delved into any links provided to study protocol documentation.

Investigating the relationship between year of publication and quality rating, ordinal regression ($\alpha = 0.05$) showed that more recent studies were rated as higher quality. Due to the heterogeneity among eligible articles in measurements of children's health outcomes and spatial interactions, the results were synthesized narratively, and not via meta-analysis.

2.4.5 Synthesis of Eligible Articles

Table 2.2 below highlights key characteristics of the 49 eligible articles, with columns for publication details, study location(s), study design, number of participants, health outcome(s), and geospatial factors such as spatial types and GPS epoch setting.

Table 2.2 – General characteristics of included articles

Author(s) (ref#)	**Year of Publication**	**Journal**	**City, Country**	**Study Design**	**Sample size (N)**	**Health Outcome(s)**	**Typology of Spaces**	**GPS epoch (seconds)**
Almanza et al (1)	2012	Health and Place	Chino, California	quasi-experimental, cross-sectional	386	MVPA	no	30
Bondo Anderson et al (2)	2015	Landscape and Urban Planning	Copenhagen, Denmark	longitudinal natural experiment	316	MVPA	schoolyard vs. not schoolyard	15
Borghese & Janssen (3)	2019	Canadian Journal of Public Health	Kingston, Ontario, Canada	cross-sectional	377	SB, MVPA	Outdoors vs. Not Outdoors	variable, i.e. intensity-triggered
Burgi et al (4)	2016	BMC Public Health	Zurich, Switzerland	cross-sectional	83	MVPA	Home, School, Park, Sport Facilities, Street	10
Burgi et al (5)	2015	PLoS One	Winterthur, Switzerland	cross-sectional	119	MVPA	Home, Street, Rec Facility, School, Outside	10
Carlson et al (6)	2015	Health and Place	Baltimore, Maryland; Washington, DC; Seattle, Washington	cross-sectional with blocking	690	MVPA, sedentary minutes/day	no	30
Carlson et al (7)	2016	Pediatrics	Baltimore, Maryland; Washington, DC; Seattle, Washington	cross-sectional	549	MVPA	no	30
Clevenger et al (8)	2019	Measurement in Physical Education and	Southwest Ohio, USA	cross-sectional	23	MVPA	Schoolgrounds: Field, Fixed Equipment, Court	1

		Exercise Science						
Collins et al (9)	2012	International Journal of Environmental Research and Public Health	Wolverhampton, England	cross-sectional	44	MVPA	Suburban vs. Rural (Home, Outside, Rec Facility, Street, Vehicles)	variable, i.e. intensity-triggered
Collins et al (10)	2015	Journal of Physical Activity and Health	West Midlands, UK	cross-sectional	75	MVPA	no	variable, i.e. intensity-triggered
Coombes et al (11)	2017	International Journal of Behavioral Nutrition and Physical Activity	Bristol, England	observational cohort	967	MVPA, sedentary minutes/day	no	10
Coombes et al (12)	2013	Health and Place	Norfolk, England	cross-sectional	100	bout MVPA and non-bout MVPA	Buildings; Roads and Pavement; Gardens; Parks, Farmland; Grassland; Woodland; Beaches	1 to 10
Cooper et al (13)	2010	International Journal of Behavioral Nutrition and Physical Activity	South West England	longitudinal	1010	MVPA	no	10
Cooper et al (14)	2010	American Journal of Preventive Medicine	London, England	longitudinal	137	MVPA	“journey” (outside the school playground) and “playground”(within the playground)	10

Dessing et al (15)	2013	International Journal of Behavioral Nutrition and Physical Activity	Amersfoort, Haarlem, Hengelo, Rotterdam and Vlaardingen, Netherlands	cross-sectional	76	MVPA	Schoolyard vs. inside School	15
Dunton et al (16)	2014	American Journal of Preventive Medicine	San Bernardino, California	quasi-experimental, cross-sectional	135	MVPA	Parks, Forests	30
Fjørtoft et al (17)	2010	Scandinavian Journal of Public Health	Gudeberg, Norway; Begby, Norway	cross-sectional	81	MVPA	no	7
Fjørtoft et al (18)	2009	Landscape and Urban Planning	Southern Norway	quasi-experimental, cross-sectional	70	MVPA	schoolyard A= small “soccer field” and the remaining asphalt area; schoolyard B = forest and an asphalt area	5
Gilliland et al (19)	2019	Spatial and Spatiotemporal Epidemiology	London, Ontario, Canada	cross-sectional	36	$PM^{2.5}$ exposure	Agricultural, Commercial, Industrial, Institutional, Recreational, Residential, Greenspace	1
Hecke et al (20)	2018	International Journal of Health Geographics	Ghent, Belgium	cross-sectional	173	MVPA	Public transportation stops/stations; Streets; Parking lots; Square; Street Shopping; Sports field/playgrounds; Parks; Shopping malls; Vacant lots	30
Jerrett et al (21)	2013	American Journal of Preventive Medicine	Chino, California	longitudinal	386	MVPA	no	30
Jones et al	2009	International Journal of Behavioral	Norfolk, England	observational cohort	100	MVPA	Buildings; Roads and Pavement; Gardens; Parks, Farmland;	variable, i.e.

(22)		Nutrition and Physical Activity					Grassland; Woodland; Beaches	intensity-triggered
Klinker et al (23)	2014	International Journal of Behavioral Nutrition and Physical Activity	Copenhagen, Denmark	cross-sectional	367	MVPA	School Grounds, Clubs, Sports Facilities, Playgrounds, Urban greenspace, Shopping Centers	15
Klinker et al (24)	2014	Frontiers in Public Health	Copenhagen, Denmark	observational cohort	523	MVPA	active living domains:leisure, school, transport, and home; subdomains: schoolgrounds, clubs, sports facilities, playgrounds, urban greenspace, shopping centers, and “other places; home domain: students’ primary addresses	15
Lachowycz et al (25)	2012	Health and Place	Bristol, England	longitudinal	902	MVPA by season	Urban Greenspace, Buildings, Roads and Pavements, Private gardens, Parks, Farmland, Grassland, Woodland, Built Surfaces	10
Lee et al (26)	2016	Preventive Medicine Reports	Vancouver, BC	observational cohort	49	MVPA	no	1
Lee et al (27)	2014	American Journal of Health Promotion	Austin, Texas	cross-sectional	131	MVPA	Home, School, Athletic facility, Entertainment venue, Greenspace, Military, Parking lot, Religious venue, Residential, Restaurant, Retail, Services, Transportation	30

Lin et al (28)	2018	BMC Public Health	Kingston, Ontario	observational cohort	433	sleep characteristics (time in bed, sleep duration, sleep chronology, and sleep efficiency)	no	15
Maddison et al (29)	2010	Pediatric Exercise Science	Auckland, New Zealand	observational cohort	79	MVPA	no	variable, i.e. intensity-triggered
Matisziw et al (30)	2016	Landscape and Urban Planning	Columbia, Missouri	observational cohort	134	MVPA	Built vs. Vegetated (Park/Open Space; Residential; Commercial; Industrial; Agricultural; Institutional; Transportation; Water)	5
McMinn et al (31)	2014	Geospatial Health	Aberdeen, Scotland	cross-sectional	166	MVPA	greenspace; road/track/path; other natural area; other man-made area	5
Nethery et al (32)	2014	Environmental Health	Montreal, Quebec	observational cohort	54	PM2.5 exposure	Home; Transiting; Outdoors; School	60
Pearce et al (33)	2018	Journal of Physical Activity and Health	Edinburgh, Scotland	observational cohort	82	MVPA	no	10
Pizarro et al (34)	2016	Journal of Transport & Health	Porto County, Portugal	cross-sectional	155	MVPA	no	15
Pizarro et al (35)	2017	Journal of Physical Activity and Health	Porto County, Portugal	observational cohort	374	MVPA, sedentary minutes/day	no	15
Quigg et al (36)	2010	Preventive Medicine	Dunedin, New Zealand	cross-sectional	184	TDPA	Parks, Playgrounds	3

Rainham et al (37)	2012	American Journal of Preventive Medicine	Halifax, Nova Scotia	observational cohort	380	MVPA	no	1
Remmers et al (38)	2019	International Journal of Environmental Research and Public Health	Hertogenbosch, Netherlands	longitudinal	255	SB, MVPA	Schools, Buildings, Roads, Playgrounds, Agriculture, Forests, Greenspace	10
Robinson & Oreskovic (39)	2013	International Journal of Health Geographics	Boston, Massachusetts	quasi-experimental	32	MVPA	no	30
Rodrıguez et al (40)	2012	Health and Place	San Diego, California; Minneapolis, Minnesota	longitudinal	293	MVPA,sedentary minutes/day	no	60
Southward et al (41)	2012	American Journal of Preventive Medicine	Bristol, England	longitudinal	141	MVPA	no	10
Stewart et al (42)	2017	Health and Place	Auckland and Wellington, New Zealand	observational cohort	196	MVPA	no	15
Tarp et al (43)	2015	Journal of Physical Activity and Health	Odense, Denmark	Randomized Controlled Trial	23	MVPA	no	5
Taylor et al (44)	2018	Children	London, Ontario; Nipigon, Ontario	observational cohort	546	MVPA	Parks, Playgrounds	1
Van Kann et al (45)	2016	Journal of School Health	Limburg, Netherlands	cross-sectional	257	MVPA, sedentary minutes/day	no	15

Van Kann et al (46)	2017	Journal of Physical Activity and Health	Netherlands	longitudinal quasi-experimental	1340	MVPA, sedentary minutes/day	no	15
Voss et al (47)	2014	Journal of Transport & Health	Vancouver, BC	observational cohort	49	MVPA	no	1
Ward et al (48)	2016	Health and Place	Auckland, New Zealand	observational cohort	118	MVPA; Life Satisfaction; Well-being; Sensation Seeking Behavior; Risk-Taking Behavior; Neuro-cognitive Development	Parks, Sports Fields, Reserves	15
Wheeler et al (49)	2010	Preventive Medicine	Bristol, England	observational cohort	1307	MVPA	Indoors, Outdoor greenspaces, Outdoor non-greenspaces	10

2.4.5.1 General Study Details

Countries where studies were conducted are predominantly in Britain (n = 12), Canada (n = 8), the United States (n = 8), Scandinavia (n = 6), New Zealand (n = 4), and the Netherlands (n = 4). Across the 49 articles, 10 were rated as Strong, 33 were rated as Moderate, and 6 were rated as Weak. Study sample sizes ranged from 23 to 1,300 participants. Study length (i.e. length of primary data collection via GPS logger) ranged from one day to thirty-three days, with a median of seven days. Eligible studies focused on one or more of six health outcomes: Cognitive Health, Sleep, Sedentary Behaviour, Total Daily Physical Activity, Moderate-Vigorous Physical Activity, and $PM^{2.5}$ exposure, with the majority of studies examining physical activity outcomes (n = 45).

Thirty-eight of the 49 included articles have observation-based or cross-sectional studies with a cohort of children, typically grouped by schools or by multiple groups located in a delineated space, like a city or region. There were only eight longitudinal studies (Bondo et al., 2015; Cooper et al., 2010; Jerrett et al., 2013; Lachowycz et al., 2012; Remmers et al., 2019; Rodriguez et al., 2012; Southward et al., 2012; Van Kann et al., 2017) and one randomized controlled trial (Tarp et al., 2015). In terms of demographic variables, studies recruited children from ages 5-18 years of age, and there was only one instance of a single-gender study (Rodriguez et al., 2012). Twenty-four out of 49 articles recorded the ethnicities of participants using at least a binary distinction between the study location's majority ethnicity and every minority ethnicity.

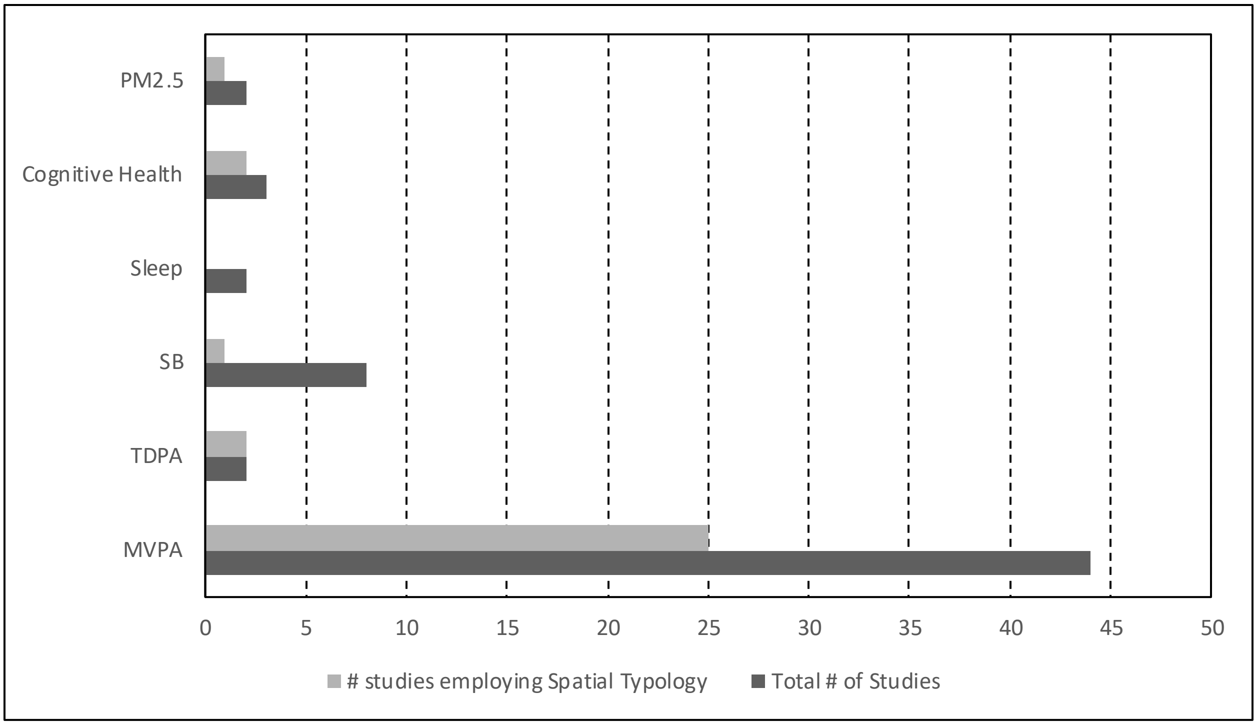

Figure 2.2 – Clustered bar chart showing frequency of different health outcomes among included studies, and frequency of those also including examination of at least a binary spatial typology. SB = Sedentary Behavior; TDPA = Total Daily Physical Activity; MVPA = Moderate-Vigorous Physical Activity; Sleep = Sleep Duration and Quality; PM2.5 = Particulate Matter 2.5 μm

As shown in Figure 2.2, eligible studies utilized six health outcomes, with a skew towards physical activity outcomes. Of the 25 studies that measured physical activity outcomes, 10 examined the outcomes when participants were present within parks and other greenspaces. Only 9 out of 49 articles included weather conditions in their analyses linking GPS locations to a range of spatial types. The weather variables typically included precipitation, temperature, and daylight hours. Four of the 9 articles that included discussion on weather conditions did so because the authors were aware of biases that may be introduced into their analyses due to "good weather only" data-collection days.

2.4.5.2 Type/Complexity of Spaces Studied

The complexity of spaces utilized in analyses of children's spatial interactions ranged from binary distinctions (e.g. Playground vs. Not Playground) (Bondo et al., 2015; Cooper et al., 2010; Dessing et al, 2015), to several land use classes (e.g. Schools, Clubs, Sports Facilities, Playgrounds, Greenspaces, Shopping Centers) (Burgi et al., 2015; Coombes et al., 2013; Gilliland et al., 2019). This range of typologies is exemplified in Figure 2.3. Twenty-four studies did not employ a spatial typology within the settings under examination. For instance, Lin et al. (2018) did not examine categories of spaces in relation to their sleep quality/duration outcomes, thus it is not known whether children in their study were exposed to certain types of spaces for certain amounts of time that could have affected their sleep quality/duration. Jerrett et al. (2013) examined physical activity levels of children within a smart growth community but did not disaggregate types of spaces within the community, thus were unable to examine relationships between where children spent time in the community and where they acquired MVPA.

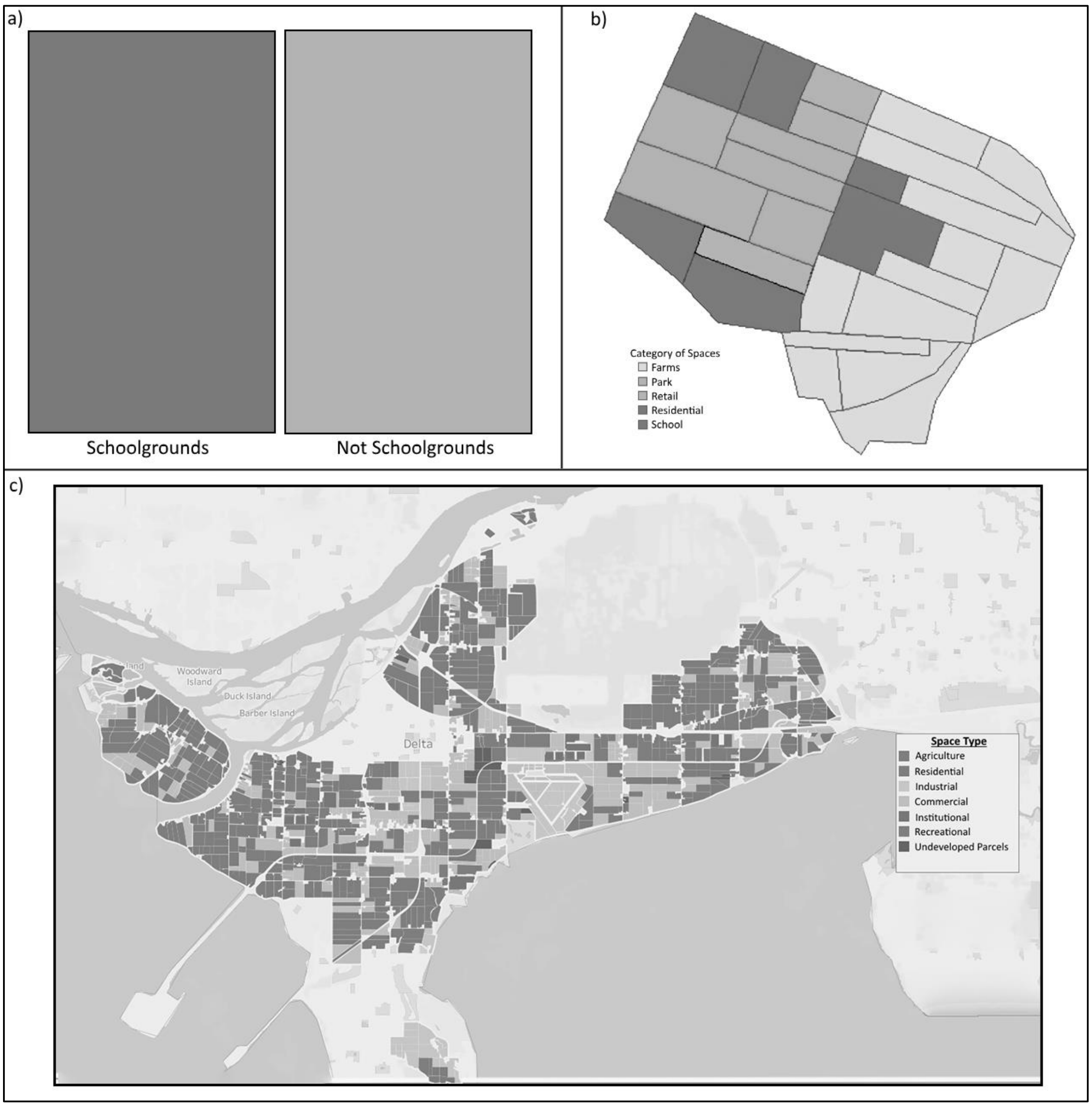

Figure 2.3 – Range in complexity of types of spaces examined in eligible articles: a) simple binary distinction, b) 5 (median) or fewer categories, c) greater than 5 categories

The utilization of GIS software in tandem with spatial typologies was not always reported by researchers using GPS. For example, Collins et al. (2012) examined MVPA as it relates to a suburban versus rural spatial dichotomy, yet the authors failed to discuss both their use of GIS to analyze the relationships between GPS points and their demarcation of suburban and rural spaces in their study locations. Sixteen articles employed spatial or spatiotemporal weighting in their analyses, such as Geographically Weighted Regression (GWR), semivariograms, and spatial clustering.

2.4.5.3 GPS Utilization

Epochs, which are the frequency at which GPS loggers are set to record a location point, were reported in all 49 articles. However, authors infrequently justified their choice of epoch (n = 31 for *Yes* or *Partially*). Where epochs are justified, they are typically discussed in the vein of preserving battery life or due to participant/environment dynamics.

Most eligible articles (n = 44) aligned their GPS parameters to best fit their specific participants, while trying to ensure measurements taken can be spatiotemporally linked to participant health outcome(s). Almanza et al. (2012) was interested in measuring moderate-vigorous physical activity (MVPA) in 8-14-year old's in Chino, California. To achieve this, the researchers set their GPS epoch to 30 seconds and linked the GPS logger to a synchronized accelerometer. In a similar study, Burgi et al. (2015), also interested in measuring MVPA in (Swiss) adolescents, set their GPS epoch to 10 seconds and synced to an accelerometer. The finest temporal resolution for GPS-accelerometer-combined MVPA studies was employed by Lee et al. (2016), who set their GPS epoch to 1 second. Of those three studies, only Burgi et al. (2015) defined a classification of spaces where their participants were exposed to or engaged within, yet all three wanted to measure adolescent activity levels and spatial influences on those levels.

Ward et al. (2016) measured an array of health outcomes, including MVPA, life satisfaction, mental well-being, and neuro-cognitive development. They employed synchronized GPS (15s epoch) and accelerometers for the MVPA outcome only. For the mental health outcomes, they employed questionnaires only, thus limiting the potential for spatiotemporal analyses of those outcomes. Nevertheless, the authors did mention that linking mental health outcomes to fine-resolution spatiotemporal data is spurious and not reasonably linkable to long-term effects.

The Physical Activity Location Measurement System (PALMS) tool, a processing tool for raw GPS data developed by Patrick (2009), was utilized by 13 out of the 49 eligible articles. It is certainly not an automatic disadvantage nor results in lower study quality to use external sources for GPS data processing, especially if resources are limited or if the external tool fits well with the nature of the data. Indeed, PALMS purports to address GPS post-processing best practices (Patrick, 2009). However, if GPS post-processing work is mainly handled by an external tool such as PALMS, it behooves researchers to "look under the hood" of such tools. Researchers should investigate what kind of training data informed the tool's development, and how effective the tool has been in contributing to outcome predictiveness. Out of the 13 articles utilizing PALMS, 5 were rated Strong and 8 were rated Moderate.

2.4.5.4 Spatiotemporal Measurements

Among the 49 included studies, 19 incorporated parks and recreation land use categories. GPS is a requirement of eligibility in this review, thus all 19 included exposure elements in their analyses. Out of those 19 studies, 11 measured accessibility of parks and recreation spaces from locations common to all their participants, such as home, school, or church. The accessibility measures ranged from use of simple Euclidean buffers, to network buffers, to census divisions; buffer distances ranged from 500m to 2500m. Predominantly in the studies, accessibility buffers acted as containers for parks and recreation spaces which were spatially joined to them. Only 6 out of the 11 studies that measured accessibility statistically compared it to measures obtained from participant GPS exposures.

The period of data collection in the studies ranged from one day to thirty-three days, with 22 studies collecting GPS data from their participants over seven consecutive days. The subdivisions of time in the included studies ranges from blocks of time in school (e.g. recess, lunch), to single days, to aggregated weekdays and weekend days. 14 studies fully segmented a child's GPS-recorded time into logical blocks, basing the blocks off survey responses from child participants regarding portions of time in their daily lives, or basing the blocks off clusters of GPS points separated by lines of points (e.g. stops broken up by routes). All of the 14 studies included GPS data from these blocks in their descriptive and inferential statistical analyses.

Very few of the included studies (n = 5) subdivided parks and recreation spaces into specific facilities or amenities, and three of the five that did so split them into a simple dichotomy (e.g. playground versus non-playground, as seen in figure 2.3). 13 of the 19 studies that utilized parks and recreation land use categories statistically analyzed relationships (e.g. bivariate analyses or multivariate modelling) between GPS-recorded exposures to them and survey or census-recorded demographic and socioeconomic variables. Only two of the five studies that subdivided parks and recreation spaces into specific facilities or amenities statistically analyzed relationships between GPS-recorded exposures to them and survey or census-recorded demographic and socioeconomic variables. None of the 49 included studies combined subdividing parks and recreation spaces into specific facilities or amenities, and subdividing child participants' GPS-recorded time into logical blocks, and then statistically analyzing relationships (e.g. bivariate analyses or multivariate modelling) between participant demographic and socioeconomic variables and their GPS-recorded exposures and engagement in such space-time blocks.

2.4.6 Discussion

To properly couple GPS data from child participants with environments relevant to the health or spatial interaction outcome(s) under investigation, there is a need for studies employing GPS logging to:

- Acquire a large enough sample size to detect statistical significance;
- Acquire a practical sample size, in essence one that accounts for potential protocol non-adherence by child participants;
- Determine amounts of time needed to collect adequate amounts of data, both per day and total number of days, to be representative of the population of children; and
- Define the full breadth of spaces that may influence health-related and/or spatial-interaction outcomes.

Subsequent to those data collection recommendations, raw GPS data from loggers requires extensive post-processing before being viable for inferential analysis (Kalkhan, 2011; Shen & Stopher, 2014; Thierry et al., 2013). To achieve such viability, there is a need for studies utilizing GPS data to understand the compromise between micromanagement of participant protocol adherence, assuring battery life, and assuring rigorous data collection. This is notable because Krenn et al. (2011) found in their systematic review that, when it comes to obtaining quality GPS data, sample sizes and epoch settings are not as critical as participant protocol adherence.

Following collection of raw GPS data, it is important to understand GPS' geometric properties, as defined by NMEA standards. These properties include Dilution of Precision (DoP) values, radial errors (error-prone points recorded during cold start of receiver), circular errors (3m resolution of 95% of points), and drift due to poor satellite alignment. Subsequently, studies should perform post-processing of raw GPS data, including removing high-DoP-value points and radial errors. Where gaps exist in GPS data that can be logically filled, studies should correct missing GPS points, such as when GPS signal is lost inside structures. Structures where gaps are filled in should relate to spaces participants frequently interact with. For children, that can be school buildings, residences, and recreation facilities.

It is important to avoid spatiotemporal biasing when correcting for missing points. Researchers should correct such points by matching to the logger's epoch, and include a rationale for how correcting missing points is performed based on gaps in distance/time from the last successfully recorded point. Once a valid set of GPS points is generated, they should be joined to a contiguous set of GIS polygons (e.g. fishnet or hexagonal spatial bins), in which the polygons are precisely tailored to spaces investigated in the study.

The complete integration of GIS data, GPS data, spatial classifications, and participant attribute data is key to examining precise environmental influences on children's health outcomes. Influences at varying levels of the SEM are critical for relating participant data to accessibility, exposure, and engagement to parks and recreation spaces. McCrorie et al. (2014, pp. 1) brings this critical aspect to attention, stating that "*A greater understanding of geographic variation (i.e. within and between countries), as well as urban/suburban and rural dwelling is welcomed, and future work should also include the investigation of psycho-social health as an outcome, as well as differences in socio-economic status, sex and adiposity.*"

When analyzing relationships between children's attributes and spatial or health-based outcomes, it is important for researchers to not just throw in a small number of demographic and socioeconomic variables that may influence the outcomes. Following in lockstep with similar previous studies and the choices they made in the utilization of independent variables does little to enhance scholarship. Rather, it is key to investigate potential influences from all variables that can be recorded from the participants being studied, including novel ones entering the research paradigm. Following that, researchers should calculate statistics to see if there is collinearity between novel variables and literature-established variables. Not following such best practices makes results spurious. Burgi et al. (2015), for example, did not incorporate children's socioeconomic measures in their investigation into spaces associated with MVPA, even though their space types included recreation facilities that employ entry fees.

Furthermore, it is critical in GPS-based studies of children to understand how time is segmented among child participants. Researchers should not assume portions of time in a child's weekdays or weekend days follow a stereotypical set of periods. Among the included studies, other than the 14 studies which fully segmented a child's GPS-recorded time into logical blocks, researchers from the remaining 35 studies either never talked about periods of time, or ascribed time to a simple model: prepare for school – travel to school – school – travel from school – travel to MVPA venue – home for dinner – homework after dinner – TV before bedtime – bedtime (Healy, 2018; Woodland, 2008). Clusters of activity garnered from GPS data and integrated with spatial bins should be joined with the aforementioned time blocks. These clusters can then be spatiotemporally analyzed for variances and correlations along with demographic/socioeconomic characteristics of participant children. For instance, even though Dunton et al. (2014) examined levels of spatial interactions in parks and forests among 8-14-year-old multiethnic Californian children, the authors did not drill-down into what segments of time were significantly spent in those greenspaces by the children.

Finally, it is incumbent upon researchers using GPS for studying children's environmental behaviors to understand variability in levels of spatial interactions. The potential for interactions in a space (e.g. accessibility), frequency of interactions in a space (e.g. exposure), and duration of interactions in a space (e.g. engagement) can be significantly influenced by the scale and sensitivity of measuring spaces and the time spent in them. Hecke et al. (2018), measuring Belgian adolescents' exposures to commercial and sports spaces, employed multilevel hurdle and gamma models to account for variability in the frequency and duration of GPS-recorded clusters in those spaces. Such modelling helped Hecke et al. determine where thresholds of significance were for levels of spatial interactions related to their outcomes.

Altogether, limitations in the children's geographies literature exist regarding GPS processing routines, understanding GPS' inherent drawbacks, utilizing precise spatial definitions or classifications, lack of key socioeconomic and demographic data, and not factoring in weather or seasonality effects. Causality is certainly difficult to infer due to selective daily mobility bias, in essence access to spaces is influenced by mobility options and personal preferences for certain activities (Chaix et al., 2013). Parks and recreation spaces do not cause health outcomes to be improved, but rather provide a venue for that potential (Alexander et al., 2013). That potential is key to improving children's overall health, therefore limitations in the literature should be addressed.

Researchers outside of geography circles – and even some inside – tend to use simplistic measurement methods to derive accessibility to parks and recreation spaces, and often use their results as a proxy for exposure. Engagement is infrequently employed in research studies of children's health outcomes, and rarely are all three (accessibility, exposure, and engagement) operationalized in a conceptual spatiotemporal framework like AEE. This thesis will fill gaps in the literature regarding measurement methods of children and their spatial interactions, particularly gaps in identifying groups of children exposed to and engaging with health-positive environments like parks and recreation spaces.

3 Methods

The purpose of this chapter is to provide a detailed description of the procedures regarding primary data collection, data processing, and data analysis of STEAM data pertaining to the four research questions. The chapter includes details on study design and recruitment, data-collection mechanisms (socio-ecological and spatial), data management and processing via GIS tools, and statistical data analysis. Socio-ecological and spatial measures are thoroughly described and linked to the thesis research questions.

3.1 The STEAM project

3.1.1 Study Design and Recruitment

The STEAM project of 2010-2013, conducted throughout southwestern Ontario, collected data on the environments children ages 9-14 years interacted with. Guided by the Socio-Ecological model (see section 1.4.1), STEAM's research design is a mixed-methods observational study, observing how children from southwestern Ontario interact with their physical environment (Richard, 2014; Taylor et al., 2018). STEAM researchers recruited schools and students through four Ontario school boards: Thames Valley District School Board, London District Catholic School Board, Conseil Scolaire Viamonde, and Conseil Scolaire Catholique Providence. The project was approved by the Non-Medical Research Ethics Board of the University of Western Ontario (NM-REB#:108029) and the research officers of the four school boards.

To recruit participants from the schools, researchers gave presentations to classes, and had children take home letters-of-intent for their parent/guardians to provide written consent. Consent was obtained from both parents/guardians and the child participant themselves. Recruitment presentations were made to 1394 students in 33 schools throughout southwestern Ontario, with 932 students (recruitment rate of 66.9%) agreeing to participate. According to the full study protocol, recruited children had their height and weight objectively measured, were fitted for an accelerometer, and were trained on how to charge and carry a GPS logger (details in section 3.1.2). To maximize data retention and participant protocol adherence, every school was visited every school day, and researchers checked over protocols with participants. The entire primary data collection process was repeated verbatim in season two with the same participants.

3.1.2 Data Collection

The research design of the STEAM project incorporates both quantitative and qualitative methods of data collection (see figure 3.1). The innovative suite of tools used for data collection include passive Global Position System (GPS) loggers, accelerometers, activity diaries, parent/child surveys, focus groups, and a GIS including a multi-layered environmental dataset (Mitchell, 2016). This thesis uses data from the GPS loggers, parent/child surveys, and GIS environmental dataset. For the purpose of this thesis, data collected on participants residing in London and surrounding small towns and rural-urban fringe of Middlesex county was used.

Figure 3.1 – STEAM data-collection mechanisms (Gilliland, 2013). This thesis utilizes data from mechanism #1 (Youth and Parent surveys) and mechanism #2 (Portable GPS)

3.1.3 Surveys

Letters of information were sent to STEAM participants and their parents/guardians and included parent and child surveys containing questions on demographic and socioeconomic variables. Parents/guardians had the option to fill out the demographic/socioeconomic survey (mechanism #1 in figure 3.1). Questions pertaining to participants' neighbourhoods were also included, such as their perceptions on the safety of local places and the quality/quantity of parks and recreation amenities. Additional questions regarding influences of weather on their activities, health related quality-of-life, and transportation options and preferences were included in the survey portion of STEAM's data collection regime. All survey questions utilized previously validated tools: Neighbourhood Quality of Life Study, Neighbourhood Environment Walkability Scale, International Physical Activity Questionnaire for Children, and the Pediatric Quality of Life Measurement Model. These tools validated answers to questions pertaining to parent/child perceptions and emotions (Cerin et al., 2006; Janz et al., 2008; Varni et al., 1999). At the conclusion of their involvement in the STEAM project, participants filled out the surveys again.

3.1.4 GPS Logging

For each participant, observation data of their locations was collected via GPS loggers for seven days over two seasons in one year (winter and spring 2010; spring and autumn 2011-2013). Participants were provided either a VisionTac VGPS-9000 or Columbus V-900 GPS logger for two weeks – one week in spring season, one week in autumn season – for their participating year. The loggers recorded date, time, latitude, longitude, speed, and geometric precision values each second the child wore the device. Participants were asked to recharge the logger every night and avoid getting it wet.

Participant home locations were derived from analysis of their GPS data using an ArcGIS kernel density function. Essentially, the residential location with the densest cluster of points during out-of-school hours was identified as their home. Using ArcGIS Desktop (Environmental Systems Research Institute, 2020), home locations were geocoded into coordinates (Clark et al., 2015; Richard, 2014). Rules for wearing the logger, which was to be turned off only during bathing, swimming, and sleeping, were inconsistently followed, hence cutoffs to be considered a valid participant were employed in analyses involving GPS data. The minimum data needed, both per day and per participant, are explained below in section 3.2.2.

3.2 Data Processing of GPS logger data

On a daily basis at each school, GPS loggers were retrieved from STEAM participants, micro-SD cards were extracted from the devices, and location data downloaded onto laptops by field technicians. Raw GPS logger data were organized into geodatabases (.gdb) in ArcGIS Catalog, with point features sorted per participant per day, and labelled by participants' school. ArcGIS Pro 2.4 and Spyder Python IDE 3.3.4 (Raybaut et al., 2019) tools were used to automate management of the raw data into demographic groups and further process the data into a useable, analyzable state. The data for each participant were segmented by day, thus participants could be considered independent based on day type. This was done because research shows an individual child's environmental exposures are significantly different when comparing weekdays after school to weekends/holidays (Maddison et al., 2010; Mitchell et al., 2016; Timperio et al., 2008).

3.2.1 Data Management

Participant GPS data was collated into separate geodatabases, with each geodatabase representing a season per year of data collection. For example, the geodatabase GPS_S2011.gdb contained all the raw GPS data of spring 2011 STEAM participants. Within each geodatabase were feature datasets labelled per school, e.g. GPS_S2011.gdb → SchoolA. Within each feature dataset were feature classes of each participant's daily GPS recordings, with the class labelled with a unique student ID (SID). In order to perform group-based analyses by day type, the GPS data in each school's feature datasets needed to be organized into feature datasets containing each individual students' GPS feature classes, with suffixes denoting the type of day (weekday or weekend day).

Using the ModelBuilder tool and additional Python code inside ArcGIS Pro 2.4, each participant's GPS points were isolated into their individual recording days, based on a string field that contained that information (e.g. WD1 = weekday #1, WED2 = weekend day #2).

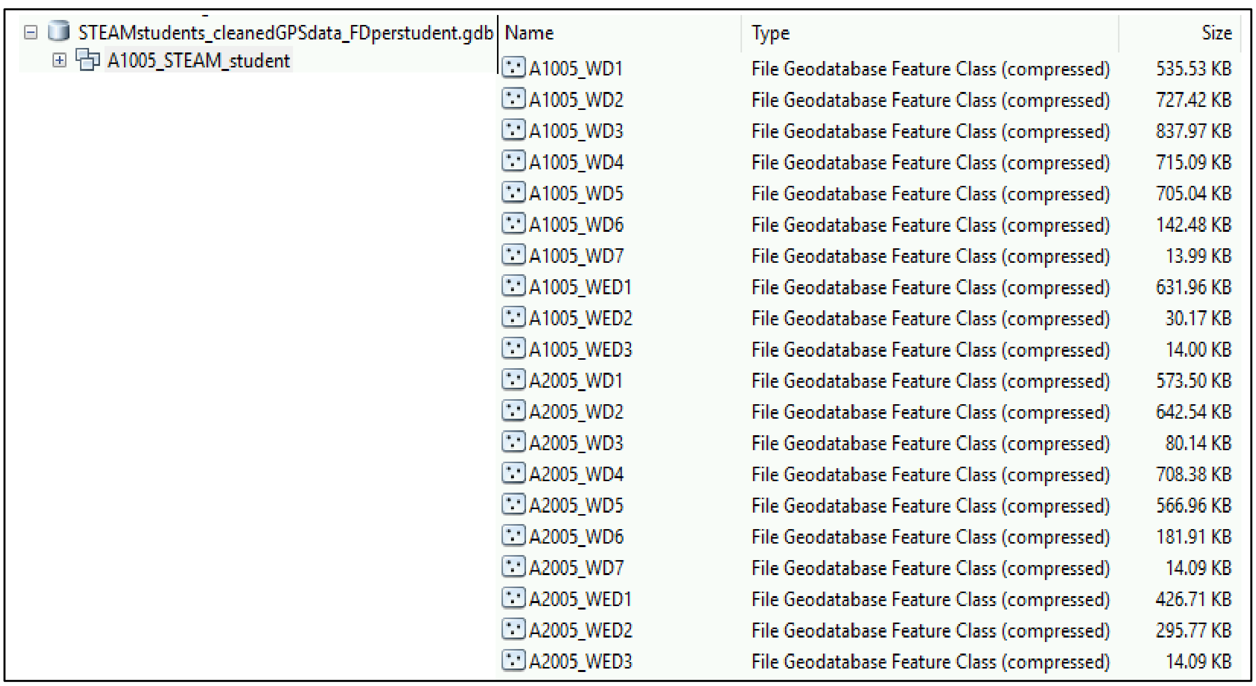

Figure 3.2 – ArcCatalog geodatabase management of STEAM participant GPS data

Feature datasets were created for each unique participant, with each dataset labelled by SID and containing feature classes of their raw GPS points, categorized and labelled by day (e.g. A1005_STEAM_student → A1005_WD1; A1005_WD2; A1005_WD3; A1005_WED1; A1005_WED2).

Universal Time Coordinated (UTC) timestamps for each GPS point were recalculated to Eastern Standard Time (EST). Based on the recorded timestamp for each GPS point, a string field called TIME_BLOCK_NAME (see figure 3.3) was populated. TIME_BLOCK_NAME flagged and binned each GPS point based on its timestamp; the processing model binned the points based on each participant's official school hours and by commonly accepted hours for meals. This processing helped determine when students had free time after school.

Field: Add Calculate Selection: Zoom To Switch Clear Delete Copy

OBJECTID	TIME_BLOCK_NAME	FREQUENCY	COUNT_TIME_BLOCK_NAME
1	AM_Home	4909	4909
2	AM_Recess	900	900
3	AM_School1	4795	4795
4	AM_School2	5692	5692
5	Lunch_Recess	2696	2696
6	PM_PostDinner	10832	10832
7	PM_PostSchool	2699	2699
8	PM_PreDinner	6147	6147
9	PM_Recess	898	898
10	PM_School1	4793	4793
11	PM_School2	3296	3296

Figure 3.3 – Snapshot of TIME_BLOCK_NAME field within each STEAM participant's GPS feature class

3.2.2 Processing GPS Quality

Removing poor quality GPS data and filling in gaps in GPS logging was done via Python scripts. These scripts were modified from GPS processing tools originally developed by Yan Kestens of the University of Montreal (Kestens et al., 2016). Kesten's ArcGIS-based toolset, called "SphereLab's Activity Place Detection Algorithm for GPS data", was designed to identify location inaccuracies and temporal gaps in consecutive GPS logger data and correct them to user-specified parameters. For this thesis, a modified version of these tools was utilized to correct location inaccuracies and temporal recording gaps from STEAM participant GPS data.

The modified version filled in gaps occurring in raw STEAM GPS data due to scatter, radial error from logger cold starts, loss of signal in-and-around structures, or inconsistent usage of the logger by participants. Between a successfully-recorded GPS point and the next successfully-recorded GPS point, the modified tool interpolated location-corrected GPS points for every second (i.e. logger epoch setting). For example, if a participant's last successfully-recorded GPS point was at the front stairs leading into an arena, then two hours later their next successfully-recorded GPS point was just inside the arena, the tool identified the arena's location as a stop (i.e. cluster of valid GPS points), and filled in the two-hour gap.

To determine a successfully-recorded GPS point, a confidence value for each point was calculated by combining attribute values of Horizontal Dilution of Precision (HDoP), Vertical Dilution of Precision (VDoP), and Positional Dilution of Precision (PDoP) geometric properties recorded by the GPS logger, plus recorded speed and number of visible satellites. Buildings have the potential to cut off GPS signal, even when the logger carried by the participant is located at the periphery of a building. Via visual analysis of a stratified-by-schools random sample of participant GPS datasets, loss of GPS signal was concentrated among points located within 30m of buildings. Many of those points recorded statistically higher-than-average Dilution of Precision values, meaning the logger recorded GPS points when the geometric configuration of satellites in the sky were obscured due to buildings.

Thus, through this visual analysis of participant raw GPS data, it was determined that any GPS point below a confidence value of 4 was considered to be providing an accurate representation of the true location of the participant (Healy, 2018). Each raw GPS point from each participant was processed through the confidence equation via Modelbuilder (see figure 3.4). Additionally, points recorded very early in the morning or very late at night were subject to excessive radial error, and thus were removed if their time stamp was before 7am EST or after 11pm EST. STEAM participants were considered to be at home and/or sleeping during those times.

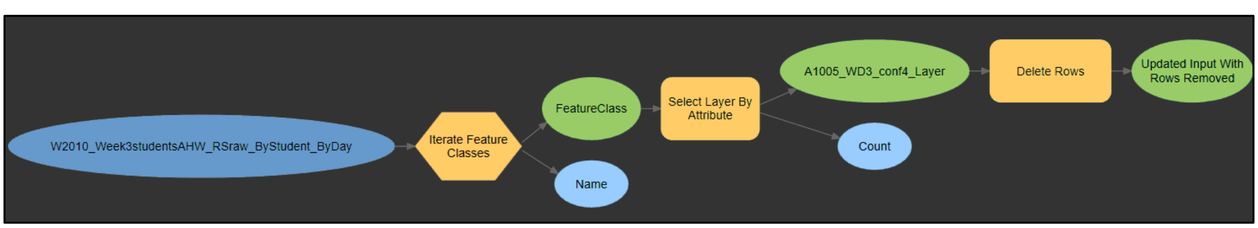

Figure 3.4 – ArcGIS Modelbuilder processing model used to remove low-confidence GPS points. The *Delete Rows* function was set to remove points (records) with confidence value > 4

To avoid biasing the GPS data used for group analyses, further post processing involved eliminating participants if they did not meet minimum GPS data cutoffs; the Modelbuilder process model for eliminating participants is seen in Figure 3.5. A participant was considered valid for this thesis if…:

- Each weekday had over three hours of processed GPS data after school hours.
- Each weekend or holiday had over four hours of processed GPS data.
- Altogether, at least four valid weekdays and two valid weekend/holiday days across the two weeks (one week in spring, one week in autumn) they were asked to wear a GPS logger.

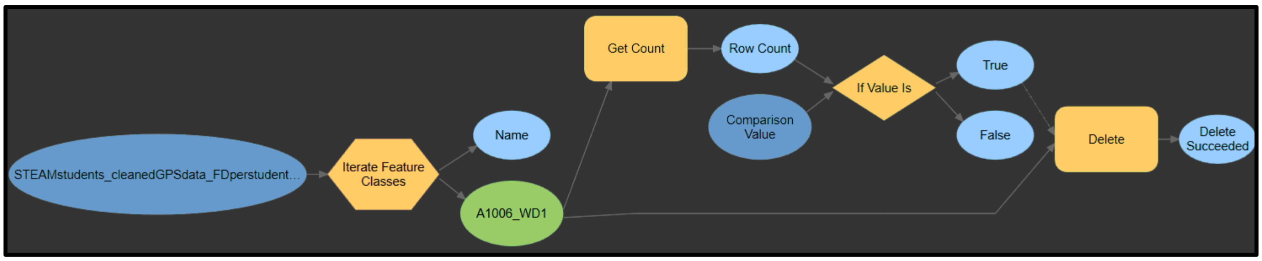

Figure 3.5 – ArcGIS Modelbuilder processing model for removing feature classes not containing minimum valid GPS data. The *Comparison Value* parameter was set to 10799 seconds for weekday feature classes (after-school time blocks), and to 14399 seconds for weekend feature classes (all blocks)

These validity requirements were, via sensitivity analysis, examined and employed by Loebach & Gilliland (2016), whom also utilized STEAM GPS data.

3.3 Measures

3.3.1 Spatial Measures

The following are descriptions of variables that have spatial components to them, thus allowing for the quantification and measurement of phenomena across Earth's surface. The variables can also be linked to participants and their characteristics as they navigate their environments. To achieve such linkages, a ~20m diameter hexagonal bin dataset was created in ArcGIS. The bin contiguously covers all land across Middlesex-London and contains all the spatial variables used in this thesis. Below is a list of categories containing spatial variables included within the hexagonal bin dataset:

- Dissemination Area household survey and general census data (Statistics Canada, 2011).

- Built and natural environment area coverage for features such as buildings, roads, parks, recreation structures, open spaces, trees.
- Normalized Difference Vegetation Index (NDVI) multispectral values for surface imagery, from Landsat 7 2011 satellite image of southwest Ontario (United States Geological Survey, Department of the Interior. LANDSAT-7, 2011).
- Area coverage for land use classes Agriculture, Commercial, Industrial, Institutional, Recreation, Residential, No Land Use (i.e. road network) (DMTI Spatial Inc., 2009).
- Area coverage for fifteen recreation types: Arenas, Baseball Diamonds, Basketball Courts, Community Centres, Football Fields, Gardens, Off-Leash Dog Parks, Outdoor Rinks, Playgrounds, Pools, Skateboard Parks, Soccer Fields, Spraypads, Swingsets, and Tennis Courts (City of London, 2019; County of Middlesex, 2019).

The spatial variables derived from the above categories are contained in spatial objects such as points (trees, recreation types) polygons (census data, land use classes, built/natural environment features, recreation types), and pixels (NDVI values). Collectively, these variables comprise the spatial measures that can be linked through GIS processes to GPS data. GPS tracks acquired from STEAM participants (mechanism #2 in Figure 3.1) are merged with the data in the hexagonal bin dataset to identify and measure daily spatial exposures, hereafter referred to as ‘daily activity spaces’. Weekday and weekend activity spaces for each participant were derived from contiguous hexagon bins containing valid GPS tracks; areas for these activity spaces were calculated in ArcGIS Pro 2.4 via summation of the area of intersected hexagon bins.

To measure counts of the fifteen recreation types accessible to participants, home location coordinates were used as origins to generate 800m, 1000m, 1500m, 2000m, 2500m, 3000m, and 4000m Euclidean and network buffers. These counts were separated into weekdays and weekend day-type groups. Where the SEM figure (see figure 4.1) shows ‘Recreation Facility within 800m of home’, the facilities include arenas, community centres, and pools, essentially the recreation types with barriers to entry and regulations for use. Urbanicity was derived from GPS-derived home locations, in which the method was previously outlined in section 3.1.4. Street connectivity refers to the number of intersections within an 800m radius of a participant’s home.

Outcome measures for the Accessibility, Exposure, and Engagement levels of spatial interactions were computed by combining the hexagonal bin dataset with both participant GPS data and GIS data on parks and recreation spaces located throughout Middlesex-London. Accessibility was calculated by buffering around participant home locations using Euclidean and network buffers. The aforementioned distances for buffers were chosen based on common distances used in the literature *and* on the City of London's Parks and Recreation Master Plan service area distances (Amoly et al., 2015; Sadler & Gilliland, 2015; Tallis et al., 2018; City of London, 2019).

Exposure was calculated in ArcGIS by combining the entire weekday or weekend GPS tracks of a participant with the hexagonal bin dataset, thus creating weekday and weekend activity spaces (i.e. contiguous set of all intersected hexagonal bins) for each participant. These weekday and weekend activity spaces were spatially joined with the parks and recreation GIS spaces, and counts of the number of intersected locations were aggregated by recreation type.

Engagement, operationalized as Exposure-plus-time-spent, was calculated similarly to Exposure, but with the addition of multiplying the amount of valid GPS tracks in each hexagonal bin by the m^2 area value for every landuse class contained in the hexagonal bin. Sums of multiplication results for weekday and weekend activity spaces provided proportions of time spent in each land use class. Furthermore, to determine free time spent in each of the fifteen parks and recreation types, the same multiplication calculation was applied with the m^2 area for each recreation type contained within intersected hexagonal bins. For further details, please refer to section 3.4 for how the measures were operationalized to answer the research questions.

3.3.2 Socio-ecological Measures

Independent variables were gathered from STEAM parent and youth surveys, 2011 StatsCan Census of Canada, and Middlesex-London GIS data. For the purpose of analyses, the variables were organized by levels of the Socio-Ecological model (see figure 4.1), including individual, interpersonal, social environment, and built environment. The variables, their potential attribute values (*italicized*), and their SEM level (**bolded**) are as follows:

- Age (*continuous value from 9-14*, **Individual**)
- Age Group (*child* ages 9-11 or *adolescent* ages 12-14, **Individual**)
- Gender (*female* or *male*, **Individual**)

- Visible Minority Status (*no* or *yes*, **Individual**)
- Dog Ownership (*no* or *yes,* **Interpersonal**)
- Asthma status (*no* or *yes,* **Individual**)
- Household Income (*low, lower-middle, middle, high*, **Interpersonal**)
- Father's Education level (so*me high school, graduated high school, graduated college/university*, **Interpersonal**)
- Mother's Education level (*some high school, graduated high school, graduated college/university*, **Interpersonal**)
- Urbanicity (*urban large city, suburban large city, urban small town, suburban small town, rural*, **Built Environment**)
- Level of Parent/Guardian Physical Activity Encouragement (*weak, moderate, strong, exceptional*, **Interpersonal**)
- Child's Perception of Number of Neighbourhood Recreation Amenities (*continuous value from 0-13,* **Individual)**
- Number of Vehicles in Home (*continuous value from 0-4,* **Interpersonal**)
- Number of Siblings (*continuous value from 0-4*, **Interpersonal**)
- Lone Parent Household (*no* or *yes*, **Interpersonal**)
- Dissemination Area Population Density (*continuous value in persons/km*^{2}*,* **Social Environment**)
- Dissemination Area Median Household Income (*continuous $CAD value,* **Social Environment**)
- Dissemination Area Proportion of Family Households Headed by Lone Parent (*continuous %,* **Social Environment**)
- Street Connectivity (*continuous*, **Built Environment**)
- Park within 800m of Home (*no* or *yes*, **Built Environment**)
- Recreation Facility within 800m of Home (*no* or *yes*, **Built Environment**)

Parent and child survey responses provided the measures needed to answer the third and fourth research questions (see section 1.5). Where survey responses were missing, imputation of missing values was calculated based on school mean or mode, or calculated using multiple imputation (see Appendix C). Based on parent and child survey responses, each participant was grouped into their socioeconomic and demographic groups. The Pandas Python library (NumFOCUS, 2019) was utilized to create code that linked participants' socioeconomic or demographic data from ArcGIS into Excel pivot tables.

3.4 Operationalizing Measures

Statistical analyses were employed to investigate relationships or group differences in STEAM participants' free time in parks and recreation spaces. For research questions #1 and #2, outcomes in the analyses were accessibility and exposure to fifteen specific types of parks and recreation amenities contained within the Recreation land use category. For research questions #3 and #4, outcomes in the analyses were proportions of free time (i.e. engagement) in parks and recreation spaces for different groups of STEAM participant children.

3.4.1 Measuring Accessibility via Buffers

To answer the first research question *"How accessible are parks and recreation spaces to children?"* and the second research question *"What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?"*, this thesis drills down into the Recreation land use category by utilizing open GIS data from the County of Middlesex and City of London. The GIS data from Middlesex-London contained location data on fifteen different types of parks and recreation amenities: Arenas, Baseball Diamonds, Basketball Courts, Community Centres, Football Fields, Gardens, Off-Leash Dog Parks, Outdoor Rinks, Playgrounds, Pools, Skateboard Parks, Soccer Fields, Spraypads, Swingsets, and Tennis Courts. Via spatial join, the GIS data was integrated with the hexagonal bin dataset, thus providing m^2 values in each hexagon that intersected a recreation amenity's parcel. Fields for both presence and m^2 area were created for each of the fifteen types.

STEAM participant home locations were incorporated into ArcGIS as point features containing all their socioeconomic and demographic variables; see figure 1.2 for set of variables. Since the first two research questions relate to the City of London Parks and Recreation policy, the number of participants analyzed was reduced to those with home locations within 800m of the circulation network of London.

To contrast the different ways that children's levels of interactions with parks and recreation spaces can be measured, this thesis compares the accessibility of Middlesex-London recreation types from STEAM participants' homes to the GPS-recorded exposure of STEAM participants with the recreation types. The accessibility measurements are then contrasted with the service areas the City of London's Parks and Recreation Master Plan outlines for each of the fifteen recreation types (City of London, 2019).

To measure accessibility, circular buffers emanating from home locations (e.g. figure 3.6) were generated in ArcGIS Pro for the following sizes, all of which match the full range of the Parks and Recreation Master Plan service areas: 800m, 1000m, 1500m, 2000m, 2500m, 3000m, 4000m. These service areas are, as explained by the City of London, to "*provide maximum coverage of recreation amenities for all children throughout London.*" (City of London, 2019). Because the service areas are essentially implemented as Euclidean buffers, and managed by a policy-making authority, this thesis uses the City of London's Parks and Recreation Master Plan service areas as justification for measurement analyses regarding accessibility. Buffers along a circulation network (i.e. London's roads/sidewalks/trails/shortcuts network dataset) were also generated from participant homes for all service area sizes. Statistically contrasting buffer measurement methods (Euclidean vs. circulation network) was performed.

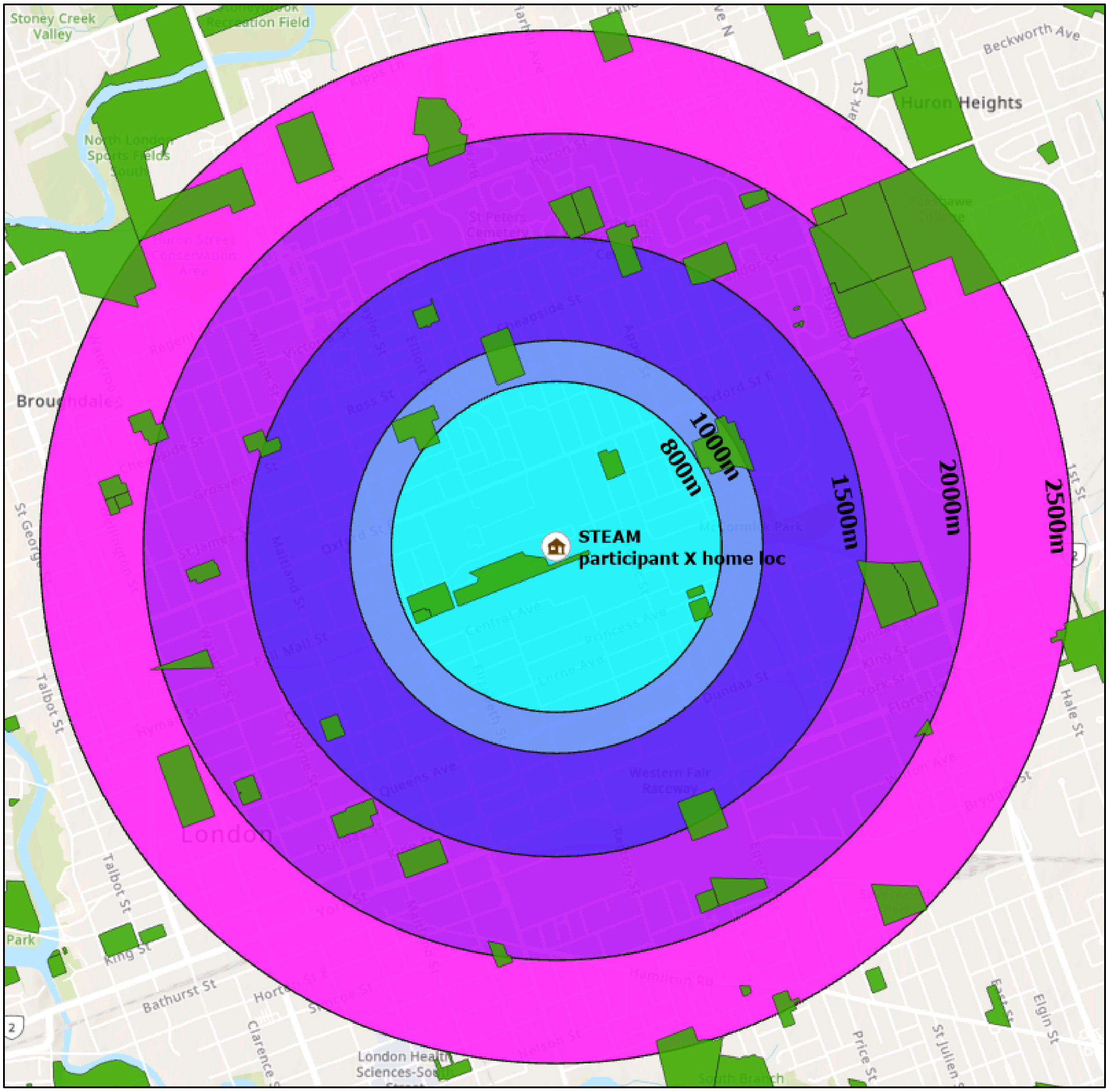

Figure 3.6 - A hypothetical STEAM participant's home location and its associated Euclidean buffers (800m – 2500m), intersected with neighbouring recreation amenities (green parcels)

For every participants' home location, counts of each of the fifteen recreation types within buffer areas were calculated via spatial join in ArcGIS Pro. The counts within each buffer area were contrasted with counts of recreation types intersecting each participants' weekday or weekend GPS tracks. As previously mentioned, these weekday or weekend GPS tracks are referred to as weekday or weekend activity spaces, and are operationalized as irregular-shaped polygons created by spatially joining aggregated GPS tracks to the hexagon bin dataset. Contrasts in counts of recreation types between the Euclidean buffers, circulation network buffers, and weekday/weekend activity spaces were statistically analyzed via Chi Squared tests. To determine how many participants have certain recreation types within the city's expected service area coverage, differences between buffers and weekday/weekend activity space exposures were contrasted with service area definitions from the City of London Parks and Recreation Master Plan.

3.4.2 Measuring Exposure via Hexagon Bins and GPS tracks

To contrast with accessibility, weekday and weekend exposure to the fifteen recreation types is operationalized as valid GPS tracks from each STEAM participant intersecting with each recreation amenity's parcel. During each of their recording days, if a participant's GPS tracks intersects with a recreation amenity, they are recorded as having been exposed to that amenity. The total volume of GPS points across the entire sample was over 100 million.

The hexagon bin dataset employed in this thesis, which contained over 12 million individual bins, has many benefits over other spatial binning options like census tracts or zoning parcels. The dataset is spatially contiguous, avoids the edge-effect, decreases impacts from the modifiable areal unit problem (Kwan, 2012b; Sadler et al., 2011), can contain both spatial and demographic variable data, and contains small-scale data that can be aggregated up to larger scales based on fluid geographic contexts (Healy, 2018; Kwan, 2012a). STEAM's hexagon bin dataset contiguously covers all of Middlesex-London with hexagons approximately 20m in diameter and with an individual area of 259.81 m^2. The hexagon dataset contains numerous spatial, land-use classification, socioeconomic, and demographic data that can be linked to the activity spaces of STEAM participants; refer to section 3.3 for the full list.

Participant exposure to the Recreation land use category was operationalized as their valid GPS tracks intersecting with hexagons. Each hexagon includes m^2 values for seven land use categories: Agriculture, Commercial, Industrial, Institutional, Recreation, Residential, and No Land Use (i.e. road network). Refer to Table 3.1 for standardized definitions of the land use categories. Daily proportions of exposure to the seven land use categories were based on GPS join count to hexagons multiplied by the m^2 value for each category in each hexagon (see example figure 3.7). For each participant, separate daily proportions were added together for weekdays and for weekends, providing each participant an average weekday and an average weekend proportion exposed to the collective land use categories (see figure 3.8).

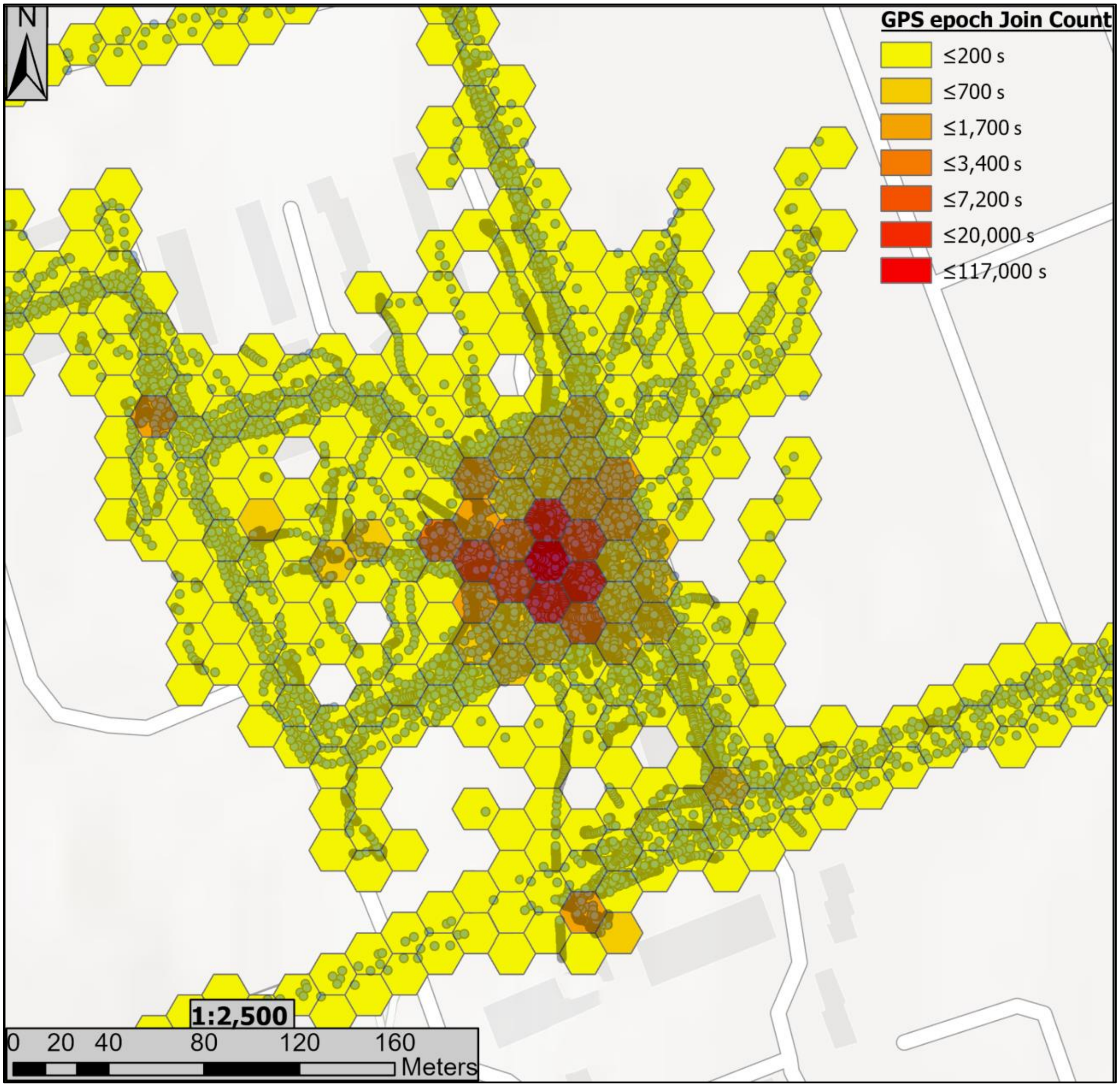

Figure 3.7 – Map showing hexagons classified by frequency of intersecting GPS points; binning method is natural breaks/jenks (Jenks, 1967). Multi-day GPS points recorded by a hypothetical participant can be seen underlying the hexagons

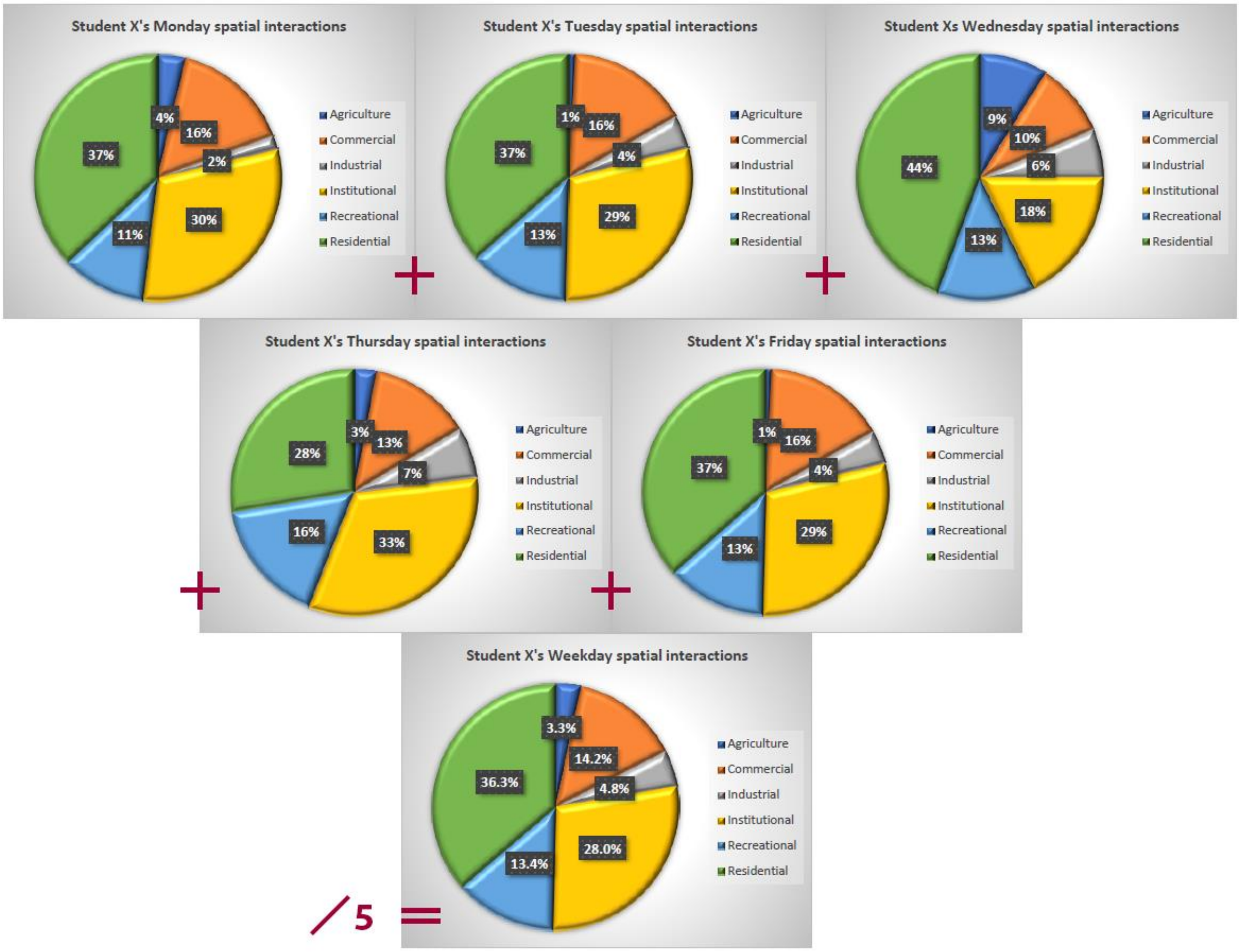

Figure 3.8 – Diagram showing process of calculating a participant's daily proportions of exposure/engagement within seven land use categories, then averaging those proportions into a weekday or weekend total proportion

Table 3.1 – Definitions of seven land use categories recorded inside the hexagon bin dataset. All land use definitions are in accordance with Ontario Ministry of Municipal Affairs government standards (2015).

Land use Category	Description
Agricultural	Land under temporary agricultural crops, temporary meadows for mowing or pasture, or land under market and kitchen gardens or temporarily fallow for less than five years.
Commercial	Land used primarily for a full range of business establishments, including shopping

	facilities, personal and service commercial facilities, offices and mixed land use developments.
Industrial	Lands used primarily for manufacturing, assembly, processing, warehousing, or storage, with associated commercial uses.
Institutional	Lands used primarily for the community, educational, health care, governmental or religious purposes.
Recreational	Land used for human leisure and activities. This includes parks, museums, greenspaces, sports fields, and sites for other activities that are not essential for human life but are pleasurable and health-improving.
Residential	Land used primarily for housing, with limited allocations for uses that are complementary to or serve basic residential uses.
No Land Use	Lands primarily used as segments and networks for travel (roads, sidewalks, boulevards, intersections) or as undeveloped (lots, buffer zones) that are either blocked from human access or are accessed in a transitional capacity between other land use categories.

3.5 Statistical Analyses

To answer the research question “*How much free time do children spend in parks and recreation spaces on (a) weekdays and (b) weekends?*”, descriptive statistics were compiled on all STEAM participants and their proportions of free time in parks and recreation spaces for aggregated weekdays and weekends. Because this question involves engagement, and not accessibility, the sample size of valid participants expanded from n = 586 (London-only sample) to n = 848 (Middlesex-London primary sample). Mann-Whitney statistics were calculated to examine significant differences between dichotomous groups of children and their proportions of free time among the fifteen recreation types, per day type (weekdays and weekends). The dichotomous groups examined were gender, visible minority status, lone-parent household, mother's education level, father's education level, and urbanicity.

To answer the research question "*What are the individual, interpersonal, and built environment factors associated with free time spent on (a) weekdays and (b) weekends in parks and recreation spaces?*", multiple linear regression modelling was performed to test the relationships between independent variables at all levels of the Socio-Ecological model (SEM), and participants' proportions of free time in parks and recreation spaces. These models were configured in hierarchical blocks that reflected the levels of the SEM. As determined via bivariate analysis with the outcome variable and with other independent variables, statistically non-significant and multicollinear variables were removed in order to develop a more parsimonious model while maintaining theoretical soundness. Multiple imputation of data for missing survey responses was performed if SPSS's Missing Value Analysis (IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.) determined responses were missing at random; this imputation approaches aligns with Madley-Dowd et al's findings (Madley-Dowd et al., 2019). The missing data analysis is outlined in Appendix C. Sample size for this research question is n = 848 (Middlesex-London primary sample).

Depending on variable distribution, Pearson/Spearman rank correlation values were calculated to examine independent variable relationships with the dependent outcome (proportion of free time in parks and recreation spaces), and to examine each independent variable with each other to see if any were collinear. Independent variables were eliminated from inclusion into multiple linear regression if they had non-significant bivariate associations with the outcome, or had high correlation ($r > 0.80$) with other independent variables and no theoretical backing to be reasonably included. Variables dropped from inclusion in models were Age Group, Asthma Status, Dissemination Area Proportion of Family Households Headed by Lone Parent, Dog Ownership, Household Income (STEAM survey), and Number of Vehicles in Home. The final set of variables included were age, gender, visible minority status, mother's education level, father's education level, lone parent household, number of siblings, parental physical activity (PA) encouragement, dissemination area population density, dissemination area median household income, urbanicity, street connectivity, whether the participant's home was within 800m of a park, and whether the participant's home was within 800m of a recreation facility (arena, community centre, pool). Due to positive skewness, the outcome variable of proportion of free time spent in parks and recreation was log transformed. Because of the log transformation, beta coefficients from the results were exponentiated.

As needed for linear regression, dummy variables were coded for multicategory independent variables. All statistical tests were processed in IBM SPSS version 25.

Table 3.2 – STEAM independent demographic and socioeconomic variables used in statistical analyses to examine relationships with dependent outcome variable *proportion of free time in parks and recreation spaces*.

Variable	**SEM Level**	**Potential Attribute Values (*reference)**
Age	Individual	continuous value ranging from 9-14
Gender	Individual	*female or male
Visible Minority Status	Individual	yes or *no
Father's Education Level	Interpersonal	some high school*, graduated high school, graduated college/university
Mother's Education Level	Interpersonal	some high school*, graduated high school, graduated college/university
Parent Physical Activity Encouragement Level	Interpersonal	weak*, moderate, strong, exceptional
Number of Siblings	Interpersonal	continuous value ranging from 0-4
Urbanicity	Built Environment	Urban, Suburban, Urban small-town, Rural small-town, Rural*

Notably absent is surveyed household income. Since only 55% of STEAM participant parents/guardians answered the question on household income, and the answers were highly correlated with Statistics Canada data on Dissemination Area Median Household Income, the surveyed household income variable was replaced in analyses with StatsCan Dissemination Area Median Household Income.

To answer the research questions "*How accessible are parks and recreation spaces to children?*" and "*What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?*", GIS data of the parks and recreation spaces was compiled from open data catalogues of County of Middlesex and City of London. The number of each type, park structure or recreation facility, was counted (see table 4.2). Both Euclidean and network buffers ranging in size from 800m – 4000m were generated from each participant's home location, and recreation locations intersecting the buffers were counted using ArcGIS spatial join function. Data tables containing counts of parks and recreation types within buffers of each participant's home location were exported from ArcGIS Pro into Excel and subsequently organized in pivot tables. Data from the pivot tables was exported into SPSS for statistical analysis. Participant sample size for these two research questions was n = 586 (London-only sample). Chi Squared tests were performed in SPSS between counts contained in each participant's home buffers (Euclidean or network), and between the counts from each participant's weekday activity space and/or weekend activity space. Significance (p) values for all statistical tests was set to 0.05, as that significance value can reveal trends in populations of children which warrant further examination (Khalilzadeh & Tasci, 2017; Mudge et al., 2012).

3.6 Conclusions

Altogether, statistical findings for all the research questions will highlight how policy matches to reality, and how differences in the ways researchers measure children's levels of interaction with parks and recreation spaces can lead to differences in accuracy. It is critical for research on children's health and health promotion to accurately determine what recreation opportunities are accessible to children and compare the accessibility to actual exposures throughout their daily lives. This thesis' research will inform better programming and planning for recreation spaces that can improve children's physical, cognitive, mental, and social health outcomes (Brussoni et al., 2020; Kweon et al., 2017; Molnar et al., 2004; Tillmann et al., 2018; Wood et al., 2013).

4 Results

This chapter reports on the results of the statistical and spatial analyses described in chapter 3, including descriptive statistics and findings from the multiple linear regression examining associations between participant independent variables and the dependent outcome of proportion of free time in parks and recreation spaces.

Section 4.1 provides descriptive statistics associated with the STEAM participants, and also delineates which variables are used in statistical analyses to answer the research questions. Sections 4.2 through 4.5 detail the calculated statistics that provide associations and comparisons which answer each of the four research questions. Each section highlights statistically significant findings among the participants and their levels of spatial interaction with parks and recreation spaces.

To refocus attention on the crux of this thesis, the research questions are:

1. *How accessible are parks and recreation spaces to children?*
2. *What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?*
3. *How much free time do children spend in parks and recreation spaces on (a) weekdays and (b) weekends?*
4. *What are the individual, interpersonal, and built environment factors associated with free time spent on (a) weekdays and (b) weekends in parks and recreation spaces?*

4.1 STEAM sample descriptive statistics

856 recruited STEAM participants provided valid free-time GPS data that met the criteria outlined in section 3.2.2. To reiterate, per participant, the criteria for validity was at least four weekdays containing at least three hours of valid GPS data recorded after the end of the school day, and at least two weekend days (also includes holidays) containing at least four hours of GPS data. Of the 856 valid participants, 848 home locations were identifiable using the ArcGIS kernel density function. This group of 848 is referred to as the Middlesex-London primary sample.

Because research questions #1 and #2 compare different ways to measure children's spatial interactions with specific parks and recreation spaces managed by the City of London, the analysis for those questions involved a further reduction of the sample. The reduction isolated

STEAM participants who lived within a reasonable distance (i.e. 800m) of the City of London boundary; the distance of 800m represents the city's smallest service area for parks and recreation amenities. The sample of the valid participants living within 800m of the City of London is 586, which is 69.1% of the GPS-valid sample with confirmed home locations.

Descriptive statistics of the Middlesex-London primary sample are displayed in Table 4.1. Within the primary sample, 56.5% of valid participants are female, 23.5% are of visible minority status, 22.4% live in a lone parent household, 87.8% have at least one sibling, and 78.4% have one parent that has graduated college/university. Age has a normal distribution centered on eleven years old, with very few participants at the outlier ages of nine and fourteen (1.9%). Fifty-five percent of participants live and attend school in the suburbs of London.

Table 4.1 – Key descriptive statistics of the Middlesex-London primary sample (n = 848)

Independent Variable	***n***	***%***
Age		
9	11	1.3
10	143	16.8
11	387	45.6
12	242	28.6
13	60	7.1
14	5	0.6
Gender		
Female	479	56.5
Male	369	43.5
Visible Minority Status		
No	649	76.5
Yes	199	23.5
Lone Parent Household		
No	658	77.6
Yes	190	22.4
Number of Siblings		
0	104	12.2

1	321	37.9
2	211	24.9
3	124	14.6
4	88	10.4
Father's Education Level		
Some High School	31	3.7
Graduated High School	268	31.6
Graduated College/University	549	64.7
Mother's Education Level		
Some High School	19	2.2
Graduated High School	164	19.3
Graduated College/University	665	78.5
Urbanicity		
Urban Large City	94	11.1
Suburban Large City	467	55.1
Urban Small Town	83	9.8
Rural Small Town	71	8.4
Rural	133	15.6

4.2 Accessibility of Parks and Recreation Spaces

The first research question, "*How accessible are parks and recreation spaces to children?*", is related to an applied policy, the City of London Parks and Recreation Master Plan, which describes service areas for fifteen different recreation types such as arenas, courts, playgrounds, pools, specialized parks, sports fields and spraypads. Table 4.2 shows the counts of each type and the service area distance applied by the Master Plan. Field sports (e.g. baseball and soccer) are the most numerous, followed by court-based sports (e.g. basketball, tennis), then by typical park amenities (e.g. playgrounds, swingsets, spraypads), then by indoor recreation facilities (e.g. arenas, community centres, pools). Specialty types – dog parks, skateboard parks, and gardens – are the rarest across London. A strong linear relationship exists between the count of a particular recreation type and the City of London's applied service area distance. In essence, the more numerous the type, the smaller the service area distance.

Table 4.2 – Count of recreation types available in the City of London, as of 2019. The accessibility of these fifteen types are operationalized by the city as Euclidean buffers.

Recreation Type	Master Plan service area (m)	Count
Arena	2000	14
Baseball Diamond	800	242
Basketball Court	1000	39
Community Centre	1500	17
Football Field	800	5
Gardens	1500	15
Off-Leash Dog Park	2500	3
Outdoor Rink	2000	2
Playground	800	136
Pool	2500	15
Skateboard Park	2000	7
Soccer Field	800	218
Spraypad	2000	29
Swingset	800	115
Tennis Court	2000	115

To measure accessibility of parks and recreation spaces from STEAM participant homes, buffer distances were chosen based on the City's full range of service areas: 800m, 1000m, 1500m, 2000m, 2500m, 3000m, and 4000m. Areas for those buffer distances are shown in table 4.3 below. Due to variability in London's circulation network (i.e. not a perfect grid pattern), the mean and standard deviation for network areas originating from participant homes is also shown in table 4.3. The mean network area is substantially less than the Euclidean area, highlighting how Euclidean buffers include inaccessible spaces in their coverage, but network buffers do not. The standard deviation of the network areas is consistently ~0.25 of the mean area, denoting that most participants live within an area where the pattern of their neighbourhood circulation network is not drastically different from the average.

Table 4.3 – Area values (km^2) for Euclidean and network buffer sizes

Buffer Size (m)	Euclidean Area (km^2)	Mean Network Area (km^2)*	SD Network Area (km^2)*
800	2.0	0.8	0.2
1000	3.1	1.2	0.3
1500	7.1	2.8	0.7
2000	12.6	5.1	1.3
2500	19.6	8.1	2.0
3000	28.3	12.0	2.8
4000	50.3	22.4	4.9

*from 586 participant homes within circulation network

Table 4.4 below shows the results of the analysis from the buffer measures (n = 586) and whether parks and recreation spaces intersect those buffers. The table outlines the proportion of participants that have at least one specific recreation type within the City of London's designated service area for that type (i.e. they are "served" by a particular recreation amenity). The Euclidean buffers are contrasted with circulation network buffers of the same distance; this contrast highlights measurement differences that can arise when using different buffer types. Wilcoxon rank-sums tests are presented that examine the difference between buffer types with the same distance value, and the proportion of participants' homes intersecting each (i.e. repeated-measures test).

Table 4.4 – Proportions of STEAM participants (n = 586) with recreation types within the City of London Parks and Recreation Master Plan service-area distances from their homes. Significance values from Wilcoxon rank-sums test for mean difference between buffer types shown in rightmost column.

Recreation Type	Master Plan service area (m)	Proportion STEAM participants' homes within service area (Euclidean buffer)	Proportion STEAM participants' homes within service area (Network buffer)	p-value for difference between Euclidean and Network buffer
Arenas	2000	68.7%	44.8%	< 0.001
Baseball Diamonds	800	87.1%	65.3%	< 0.001
Basketball Courts	1000	62.1%	40.5%	< 0.001
Community Centres	1500	51.0%	25.3%	< 0.001
Football Fields	800	5.0%	1.2%	< 0.001

Gardens	1500	49.0%	26.9%	< 0.001
Off-Leash Dog Parks	2500	36.3%	11.2%	< 0.001
Outdoor Rinks	2000	8.1%	5.3%	< 0.001
Playgrounds	800	88.5%	61.4%	< 0.001
Pools	2500	89.9%	69.9%	< 0.001
Skateboard Parks	2000	40.2%	16.6%	< 0.001
Soccer Fields	800	85.5%	62.5%	< 0.001
Spraypads	2000	87.8%	65.5%	< 0.001
Swingsets	800	83.5%	54.7%	< 0.001
Tennis Courts	2000	96.8%	78.4%	< 0.001

Among all recreation types accessible to the 586-participant sample, Wilcoxon tests showed significant differences between Euclidean and network buffer methods. These significant differences are reflected in the proportion values for each recreation type when using different buffer methods, controlling for buffer distance. As expected, Euclidean buffers intersect more participants' homes than do network buffers, regardless of recreation type or service area distance. Euclidean buffers, however, fail to address the fact that children cannot take straight-line paths to recreation destinations, but rather must use the circulation network of streets, sidewalks, and multiuse paths to navigate to recreation destinations.

Furthermore, when looking at different buffer types, most recreation types show over 20% difference in proportion of participants' homes in range of them. This difference is notably seen in the top three most numerous types: baseball diamonds (n = 242; difference in buffer type proportion = 22.6%), soccer fields (n = 218; difference in buffer type proportion = 23.8%), and playgrounds (n = 136; difference in buffer type proportion = 27.1%). As mentioned, these analyzed differences are for a subset of STEAM participants residing within or on the edge of the City of London, thus have no substantial urbanicity difference due to home locations that would spatially bias results.

4.3 Accessibility versus Exposure

The second research question, "*What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?*", builds upon the results from the first research question, and contrasts them with valid GPS exposures of STEAM participants to the fifteen recreation types described and measured in section 4.2. These free-time exposures are broken down by weekday and weekend day types, as research has shown children's spatial interactions differ significantly when comparing their after-school weekdays to their weekend days (Maddison et al., 2010; Mitchell et al., 2016; Timperio et al., 2008). Because they intersect with the hexagon bin dataset (see figure 3.7), GPS exposures can be operationalized as weekday or weekend activity spaces, with their areas calculated from the summation of areas of all intersected hexagon bins. Across valid participants, the weekday activity space mean (median) area is 34.3 km^2 (23.8 km^2), with a standard deviation (range) of 58.0 km^2 (115.4 km^2). The weekend activity space mean (median) area is 64.4 km^2 (41.3 km^2), with a standard deviation (range) of 108.7 km^2 (204.7 km^2). Across valid participants, the weekday activity space mean (median) length along longest axis is 10.6 km (8.3 km), with a standard deviation (range) of 11.7 km (26.1 km). The weekend activity space mean (median) length along longest axis is 15.3 km (11.2 km), with a standard deviation (range) of 14.2 km (30.3 km). These area and distance average values signify large variation among participants. Nonetheless, when contrasting measurements between different parks and recreation types and their buffers, any participant weekday or weekend activity spaces extending outside of London are immaterial.

Table's 4.5 and 4.6 expand upon table 4.4 by including all possible buffer distances for each recreation type, and then determining what proportions of STEAM participant's homes intersect each recreation type at those distances. The rightmost column in the tables are exposure data from participant GPS tracks. The columns include the proportion of STEAM participants whose GPS tracks intersected with each recreation type at least once during their weekdays or weekend days.

Table 4.5 – Proportion of STEAM participants (n = 586) having recreation types within various buffer distances from their homes. Proportion of STEAM participants exposed at least once during their weekdays on rightmost column.

Recreation Type	Master Plan Service Area (m)	800m Euclidean	800m Network	1000m Euclidean	1000m Network	1500m Euclidean	1500m Network	2000m Euclidean	2000m Network	2500m Euclidean	2500m Network	Exposed during weekdays
Arena	2000	15.6%	8.0%	23.0%	11.7%	49.6%	24.6%	68.7%	44.8%	75.0%	59.3%	30.9%
Baseball Diamond	800	87.1%	65.3%	92.4%	77.9%	98.1%	91.3%	98.9%	96.6%	99.5%	98.6%	96.1%
Basketball Court	1000	55.0%	29.6%	62.1%	40.5%	85.3%	63.9%	95.6%	82.8%	97.7%	92.0%	45.5%
Community Centre	1500	17.9%	5.1%	29.0%	8.8%	51.0%	25.3%	70.4%	40.4%	82.8%	52.7%	52.0%
Football Field	800	5.0%	1.2%	6.5%	3.7%	11.7%	6.4%	18.6%	9.6%	24.6%	14.3%	18.2%
Garden	1500	24.8%	11.3%	31.3%	15.8%	51.0%	26.9%	65.3%	40.0%	76.1%	48.7%	31.4%
Off-Leash Dog Park	2500	0.7%	0.0%	2.3%	0.0%	8.8%	2.8%	18.2%	5.1%	36.3%	11.2%	10.7%
Outdoor Rink	2000	0.7%	0.2%	1.4%	1.1%	4.4%	3.0%	8.1%	5.3%	12.2%	8.7%	6.1%
Playground	800	88.5%	61.4%	97.0%	75.9%	99.6%	95.4%	99.6%	99.6%	99.6%	99.6%	82.7%
Pool	2500	28.0%	8.5%	40.9%	13.6%	70.8%	33.6%	84.1%	51.2%	89.9%	69.9%	33.9%
Skateboard Park	2000	5.8%	3.7%	8.8%	4.8%	21.8%	8.5%	40.2%	16.6%	57.3%	27.8%	18.4%
Soccer Field	800	85.5%	62.5%	91.5%	74.7%	97.7%	89.0%	99.1%	92.9%	99.6%	98.1%	96.4%
Spraypad	2000	38.8%	19.5%	50.8%	27.6%	75.6%	48.5%	87.8%	65.5%	92.9%	77.5%	52.3%
Swingset	800	83.5%	54.7%	93.5%	68.7%	99.1%	92.2%	99.6%	98.4%	99.6%	99.1%	78.6%
Tennis Court	2000	45.5%	19.1%	62.7%	29.4%	91.5%	57.0%	96.8%	78.4%	98.4%	90.3%	65.9%

Table 4.6 – Proportion of STEAM participants (n = 586) having recreation types within various buffer distances from their homes. Proportion of STEAM participants exposed at least once during their weekends on rightmost column.

Recreation Type	Master Plan Service Area (m)	800m Euclidean	800m Network	1000m Euclidean	1000m Network	1500m Euclidean	1500m Network	2000m Euclidean	2000m Network	2500m Euclidean	2500m Network	Exposed during weekends
Arena	2000	15.6%	8.0%	23.0%	117%	49.6%	24.6%	68.7%	44.8%	75.0%	59.3%	23.9%
Baseball Diamond	800	87.1%	65.3%	92.4%	77.9%	98.1%	91.3%	98.9%	96.6%	99.5%	98.6%	80.7%
Basketball Court	1000	55.0%	29.6%	62.1%	40.5%	85.3%	63.9%	95.6%	82.8%	97.7%	92.0%	29.5%
Community Centre	1500	17.9%	5.1%	29.0%	8.8%	51.0%	25.3%	70.4%	40.4%	82.8%	52.7%	44.5%
Football Field	800	5.0%	1.2%	6.5%	3.7%	11.7%	6.4%	18.6%	9.6%	24.6%	14.3%	13.2%
Garden	1500	24.8%	11.3%	31.3%	15.8%	51.0%	26.9%	65.3%	40.0%	76.1%	48.7%	20.9%
Off-Leash Dog Park	2500	0.7%	0.0%	2.3%	0.0%	8.8%	2.8%	18.2%	5.1%	36.3%	11.2%	9.3%
Outdoor Rink	2000	0.7%	0.2%	1.4%	1.1%	4.4%	3.0%	8.1%	5.3%	12.2%	8.7%	5.9%
Playground	800	88.5%	61.4%	97.0%	75.9%	99.6%	95.4%	99.6%	99.6%	99.6%	99.6%	64.8%
Pool	2500	28.0%	8.5%	40.9%	13.6%	70.8%	33.6%	84.1%	51.2%	89.9%	69.9%	23.8%
Skateboard Park	2000	5.8%	3.7%	8.8%	4.8%	21.8%	8.5%	40.2%	16.6%	57.3%	27.8%	16.3%
Soccer Field	800	85.5%	62.5%	91.5%	74.7%	97.7%	89.0%	99.1%	92.9%	99.6%	98.1%	80.9%
Spraypad	2000	38.8%	19.5%	50.8%	27.6%	75.6%	48.5%	87.8%	65.5%	92.9%	77.5%	39.1%
Swingset	800	83.5%	54.7%	93.5%	68.7%	99.1%	92.2%	99.6%	98.4%	99.6%	99.1%	62.7%
Tennis Court	2000	45.5%	19.1%	62.7%	29.4%	91.5%	57.0%	96.8%	78.4%	98.4%	90.3%	45.5%

When contrasting buffers with GPS exposure data, there are notable differences. For instance, exposure to baseball diamonds and soccer fields is higher than even the smallest service area, regardless of day type. Exposures to community centres exceeds the proportions within both buffers when contrasting with the city's service area of 1500m, but only on weekdays. Exposure to playgrounds and their incorporated swingsets exceeds service area buffer proportions only on weekends. Differences between exposure proportions and buffer proportions are tens of percentage points different for most other recreation types' service areas. Specific types of recreation amenities that have barriers to entry, such as fences or required equipment, have large (> 25%) differences between buffer proportions and exposure proportions. These specific types include basketball courts, tennis courts, off-leash dog parks, and skateboard parks.

Table 4.7 presents Chi Squared test statistics that examine if participants' weekday or weekend exposures to the fifteen different recreation types matches with whether their home is within the city's service area buffer of that recreation type. Essentially, table 4.7 examines the proportion percentages in table's 4.5 and 4.6 for statistically significant differences (significant Chi Squared values) between buffer counts and counts of weekday or weekend exposures. In this series of Chi Squared tests, the *expected* values are defined by those participants who have homes within the service areas of each recreation type. It is hypothesized that they will be exposed to the nearest location of each type at least once within their weekday activity space, and at least once within their weekend activity space. In the case of the Chi Squared tests, these activity spaces are the *observed* values. Essentially, this table shows significant differences, per recreation type, between *expected* exposures and *observed* exposures from participants (n = 586) that have a home within the city's service area distances, throughout their weekdays and weekends.

Table 4.7 – Chi Squared tests showing, per day type, whether observed GPS exposures to recreation types from STEAM participants (n = 586) are matching to expected exposures as defined by the City of London Parks and Recreation service area distances. Weekday exposures are also tested for matches to weekend exposures on rightmost column.

Recreation Type	**Master Plan service area (m)**	**Pearson's Chi Squared tests**		
		Service Area distance vs. Weekday exposures	Service Area distance vs. Weekend exposures	Weekday exposures vs. Weekend exposures
Arena	2000	$\chi2 = 12.22$**	$\chi2 = 0.24$	$\chi2 = 28.88$**
Baseball Diamond	800	$\chi2 = 0.56$	$\chi2 = 0.44$	$\chi2 = 23.29$**
Basketball Court	1000	$\chi2 = 51.85$**	$\chi2 = 23.04$**	$\chi2 = 49.60$**
Community Centre	1500	$\chi2 = 7.39$*	$\chi2 = 2.11$	$\chi2 = 37.07$**
Football Field	800	$\chi2 = 15.72$**	$\chi2 = 13.24$**	$\chi2 = 39.71$**
Gardens	1500	$\chi2 = 55.89$**	$\chi2 = 18.64$**	$\chi2 = 47.17$**
Off-Leash Dog Park	2500	$\chi2 = 8.44$*	$\chi2 = 9.41$*	$\chi2 = 84.66$**
Outdoor Rink	2000	$\chi2 = 43.81$**	$\chi2 = 4.72$*	$\chi2 = 5.17$*
Playground	800	$\chi2 = 3.79$*	$\chi2 = 0.79$	$\chi2 = 43.11$**
Pool	2500	$\chi2 = 2.60$	$\chi2 = 0.03$	$\chi2 = 42.41$**
Skateboard Park	2000	$\chi2 = 5.69$*	$\chi2 = 3.88$*	$\chi2 = 28.33$**
Soccer Field	800	$\chi2 = 1.84$	$\chi2 = 1.73$	$\chi2 = 28.23$**
Spraypad	2000	$\chi2 = 4.40$*	$\chi2 = 2.59$	$\chi2 = 37.90$**
Swingset	800	$\chi2 = 0.06$	$\chi2 = 0.02$	$\chi2 = 36.76$**
Tennis Court	2000	$\chi2 = 0.17$	$\chi2 = 0.14$	$\chi2 = 42.35$**

*$p < .05$, **$p < .001$.

The most noticeable result highlighted in table 4.7 is that, when comparing to the observed exposures (GPS), the expectation that participants will be exposed at least once on both weekdays and weekends to each recreation type, the observed exposures differs significantly among all recreation types. In essence, participants are exposed to each recreation type either on weekdays or weekends, but not on both day types. This emphasizes the dichotomous nature of spatial interactions children experience during either their weekday after-school or weekend free-time periods.

Pertaining to *expected* versus *observed* differences among specific recreation types, there are numerous significant findings. When looking at collections of types such as park amenities (playgrounds, spraypads, swingsets, sports fields) or recreation facilities (arenas, community centres, pools), no significant relationships exist, either among day type or level of significance. Looking at specific recreation types, those expected to be exposed to arenas on weekdays are significantly different from those measurably exposed; the difference is not significant on weekends. Similar to the findings for arenas are the findings for community centres, playgrounds, and spraypads. The recreation types where both weekday and weekend observed exposures do not match expected exposures include basketball courts, football fields, gardens, off-leash dog parks, outdoor rinks, and skateboard parks. Notably, five of these six types are among the least numerous recreation spaces available throughout London (see table 4.2).

Such measurement differences highlight potential mismeasurement of proportions of populations being "served" parks and recreation amenities, especially when using buffers as proxies for providing children those amenities. To match to actual proportions of children being exposed to the amenities, many recreation type's service areas would need to adjust distances (i.e. increase count of amenities to provide more coverage) in order to capture proportions of children statistically equivalent to those measured from GPS exposures.

4.4 Engagement with Parks and Recreation Spaces

During weekdays and weekends, among STEAM participants (n = 848) the mean proportion of free time spent in the Recreation land use category is 4.4% (minimum 0.5%, maximum 75.0%, standard deviation 5.5%). For each participant, time-weighted proportions of their exposures to the fifteen recreation types were calculated. These exposures are all contained within the Recreation land use category and summing the proportions of free time spent in the fifteen recreation types adds up to the entire time a STEAM participant spends in the Recreation land use category. This approach answers research question #3 *"How much free time do children spend in parks and recreation spaces on (a) weekdays and (b) weekends?"*. Table 4.8 below shows descriptive statistics for participant proportions of free time (i.e. engagement) with each of the fifteen recreation types.

Table 4.8 – Descriptive statistics of proportions of participant engagement (n = 848) with fifteen recreation types.

Recreation Type	Weekdays				Weekends			
	Mdn	IQR	Min	Max	Mdn	IQR	Min	Max
Arena	0.0%	0.0%	0.0%	98.6%	0.0%	0.0%	0.0%	99.5%
Baseball Diamond	21.3.%**	44.1%	0.0%	100.0%	3.7%**	27.7%	0.0%	100.0%
Basketball Court	0.0%**	0.2%	0.0%	42.1%	0.0%**	0.0%	0.0%	70.0%
Community Centre	0.0%	0.3%	0.0%	100.0%	0.0%	1.1%	0.0%	100.0%
Football Field	0.0%	0.0%	0.0%	46.3%	0.0%	0.0%	0.0%	46.4%
Gardens	0.0%*	0.0%	0.0%	41.5%	0.0%*	0.0%	0.0%	100.0%
Off-Leash Dog Park	0.0%	0.0%	0.0%	69.1%	0.0%	0.0%	0.0%	81.8%
Outdoor Rink	0.0%	0.0%	0.0%	95.7%	0.0%	0.0%	0.0%	93.6%
Playground	0.5%*	12.2%	0.0%	100.0%	0.0%*	12.6%	0.0%	100.0%
Pool	0.0%*	0.0%	0.0%	97.5%	0.0%*	0.0%	0.0%	98.8%
Skateboard Park	0.0%	0.0%	0.0%	40.6%	0.0%	0.0%	0.0%	41.1%
Soccer Field	20.4%**	41.5%	0.0%	100.0%	10.2%**	33.3%	0.0%	100.0%
Spraypad	0.0%*	0.3%	0.0%	28.0%	0.0%*	0.2%	0.0%	31.3%
Swingset	0.2%*	8.7%	0.0%	50.0%	0.0%*	9.0%	0.0%	66.7%
Tennis Court	0.0%**	4.5%	0.0%	99.5%	0.0%**	0.9%	0.0%	56.4%

*significant difference between day type engagement at p < .01 (**p < .001) via Mann-Whitney U test statistics

Median and interquartile range values denote the spread of participant proportions in each of the fifteen recreation types. Within participants, the range among all recreation types is from 0% exposure to 100% exposure; 100% exposure represents a child spending all their GPS-recorded time in the Recreation land use category exposed to only one recreation type. For certain recreation types, daily weather effects and personal preferences may play a part in making ranges small or large. Among all recreation types, the interquartile range exceeds the median value, highlighting how skewed exposures to recreation types are among validated STEAM participants. Indeed, a positive-skewed distribution is present for all fifteen types, on both weekdays and weekends, and is exemplified by the median being 0.0% for the majority of recreation types (i.e. no engagement among at least half of participants). Baseball diamonds and soccer fields have the largest medians and interquartile ranges. This may be due to their large spatial footprints and their ubiquity throughout London, as they are the most numerous of the fifteen recreation types.

Table 4.9 highlights mean differences in proportions of free time spent in the fifteen different recreation types. Further on in table 4.10 through to table 4.15, six independent variables were dichotomized into two groups to statistically examine average differences in proportions. The dichotomous groups include gender (female or male), visible minority status (no or yes), lone parent household (no or yes), mother's education level (graduated college/university or not), father's education level (graduated college/university or not), and urbanicity (urban/suburban or small town/rural). Dichotomization was chosen as sensitivity analysis found that splitting into two groups revealed statistical significance while maintaining theoretical soundness.

Table 4.9 – Differences between mean proportions of free time spent engaged in fifteen recreation types, for six independent variables with dichotomous values

Recreation Type	Differences in mean proportions between dichotomous groups					
	Gender [i]	**Visible Minority Status** [ii]	**Lone-Parent Household** [iii]	**Mother's Level of Education** [iv]	**Father's Level of Education** [v]	**Urbanicity** [vi]
Weekday Engagement						
Arenas	0.4%	0.7%	-0.4%	-1.0%	0.2%	-0.1%
Baseball Diamonds	1.7%	-8.0%	-1.1%	1.9%	-3.5%	25.5%
Basketball Courts	0.2%	-0.4%	0.9%	0.1%	0.4%	1.8%
Community Centres	0.5%	0.0%	-0.4%	-0.6%	-0.9%	0.3%
Football Fields	0.3%	-1.5%	0.2%	-0.7%	-0.2%	0.2%
Gardens	0.5%	-0.6%	0.8%	0.2%	0.4%	0.7%
Off-Leash Dog Parks	0.4%	0.1%	0.0%	0.2%	0.2%	0.2%
Outdoor Rinks	-0.2%	-0.1%	0.2%	-0.1%	0.1%	-0.6%
Playgrounds	0.7%	0.8%	0.7%	-0.2%	0.4%	7.3%
Pools	1.1%	-0.5%	0.7%	-0.3%	-0.4%	0.7%

Skateboard Parks	0.2%	-0.4%	0.6%	0.1%	0.2%	0.6%
Soccer Fields	1.7%	-9.9%	-1.7%	0.3%	-5.9%	22.5%
Spraypads	0.3%	0.3%	1.0%	-0.7%	0.1%	0.9%
Swingsets	1.1%	-0.5%	1.0%	-0.8%	0.1%	4.4%
Tennis Courts	1.0%	-1.0%	1.4%	0.2%	-0.3%	4.0%
Weekend Engagement						
Arenas	-0.3%	1.3%	-1.0%	-0.2%	1.1%	1.8%
Baseball Diamonds	0.6%	-5.5%	2.8%	3.8%	-2.1%	15.4%
Basketball Courts	-0.03%	-0.5%	-0.3%	-0.2%	-0.6%	2.3%
Community Centres	0.1%	-1.9%	-1.4%	0.1%	-1.2%	2.7%
Football Fields	-0.2%	-0.6%	0.03%	-0.6%	-0.4%	1.0%
Gardens	-0.4%	0.1%	0.5%	0.3%	0.4%	1.4%
Off-Leash Dog Parks	-0.01%	0.3%	-0.2%	0.5%	0.1%	0.3%
Outdoor Rinks	0.5%	-0.5%	-0.4%	-0.03%	-0.1%	0.4%
Playgrounds	1.3%	-1.0%	-2.5%	-1.9%	-1.8%	7.7%
Pools	0.1%	-1.4%	0.3%	-0.8%	-1.0%	2.0%
Skateboard Parks	0.4%	0.01%	0.02%	-0.3%	0.1%	0.5%
Soccer Fields	0.2%	-6.1%	0.2%	-0.2%	-3.7%	14.1%
Spraypads	0.7%	-1.7%	0.1%	-0.5%	-0.4%	1.5%
Swingsets	0.8%	-1.8%	-0.9%	-1.4%	-1.1%	5.4%
Tennis Courts	0.5%	-0.3%	0.3%	-1.5%	-0.9%	3.8%

i – reference group is female
ii – reference group is not visible minority (i.e. Caucasian)
iii – reference group is lone-parent household
iv – reference group is Did not graduate college or university
v – reference group is Did not graduate college or university
vi – reference group is urban/suburban

Mann-Whitney statistics were compiled to examine differences between the dichotomous groups and their proportions of free time among the fifteen recreation types, per day type. These statistics are displayed in tables 4.10 to 4.15.

Table 4.10 – Mann-Whitney tests for gender differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is female.

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	81628.0	0.010	88363.5	0.996
Baseball Diamond	82327.5	0.084	84225.0	0.228
Basketball Court	80831.0	**0.011**	84956.0	0.181
Community Centre	78358.0	**0.001**	81030.0	**0.015**
Football Field	85473.0	0.174	88314.5	0.975
Gardens	81799.5	**0.012**	85738.0	0.256
Off-Leash Dog Park	85411.0	0.081	88297.0	0.962
Outdoor Rink	88011.5	0.789	86428.5	0.125
Playground	79628.5	**0.011**	81885.5	**0.049**
Pool	76594.5	**0.000**	84720.5	0.125
Skateboard Park	85811.5	0.228	82887.5	**0.007**
Soccer Field	82046.5	0.071	85615.5	0.423
Spraypad	81407.0	**0.025**	80979.0	**0.010**
Swingset	79531.0	**0.009**	81956.0	**0.049**
Tennis Court	78211.5	**0.002**	80411.5	**0.008**

significance at $p < .05$ is bolded

Mean percentage differences between genders are small, with the largest being 1.7% greater proportion for females exposed to soccer fields on weekdays. The Mann-Whitney scores show significant differences in proportions of free time in courts, community centres, and typical playground amenities.

Table 4.11 – Mann-Whitney tests for visible minority differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is not visible minority (i.e. Caucasian).

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	62438.0	0.974	59470.5	0.138
Baseball Diamond	61685.0	0.779	59818.5	0.352

Basketball Court	56158.0	**0.011**	61916.0	0.782
Community Centre	61798.5	0.787	56318.5	**0.015**
Football Field	59517.0	0.096	62285.0	0.889
Gardens	57723.5	**0.031**	62316.0	0.921
Off-Leash Dog Park	60348.0	0.130	61024.0	0.279
Outdoor Rink	62442.0	0.953	61841.5	0.531
Playground	57271.5	0.070	56980.0	**0.046**
Pool	59849.0	0.238	62305.5	0.919
Skateboard Park	57442.0	**0.005**	62054.0	0.790
Soccer Field	60172.5	0.427	62154.5	0.902
Spraypad	56808.0	**0.029**	62365.5	0.952
Swingset	56694.0	**0.043**	58152.5	0.112
Tennis Court	55861.5	**0.016**	61405.5	0.660

significance at $p < .05$ is bolded

Among visible minority status, larger mean differences show up in exposures to baseball diamonds and soccer fields, the two most numerous recreation amenities in London. Additionally, on weekends, mean differences increase for building-based recreation amenities such as arenas, community centres and pools. Mann-Whitney scores show significant weekday differences in proportions of free time in courts, gardens, and typical playground amenities.

Table 4.12 – Mann-Whitney tests for lone-parent household differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is lone-parent household.

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	62438.0	0.974	59470.5	0.138
Baseball Diamond	61685.0	0.779	59818.5	0.352
Basketball Court	56158.0	**0.011**	61916.0	0.782
Community Centre	61798.5	0.787	56318.5	**0.015**
Football Field	59517.0	0.096	62285.0	0.889
Gardens	57723.5	**0.031**	62316.0	0.921
Off-Leash Dog Park	60348.0	0.130	61024.0	0.279
Outdoor Rink	62442.0	0.953	61841.5	0.531

Playground	57271.5	0.070	56980.0	**0.046**
Pool	59849.0	0.238	62305.5	0.919
Skateboard Park	57442.0	**0.005**	62054.0	0.790
Soccer Field	60172.5	0.427	62154.5	0.902
Spraypad	56808.0	**0.029**	62365.5	0.952
Swingset	56694.0	**0.043**	58152.5	0.112
Tennis Court	55861.5	**0.016**	61405.5	0.660

significance at p < .05 is bolded

Among the parental situation in participant homes, the percentage mean differences are low in absolute value, yet there are notable statistical differences. Participants living in lone-parent homes spend significantly less proportion of their free time on playgrounds on weekends; the same significance is seen on weekends for community centres. Participants living in lone-parent homes spend significantly more proportion of their free time on courts and typical playground amenities on weekdays.

Table 4.13 – Mann-Whitney tests for mother's education level differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is Did not graduate college or university.

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	63313.0	0.153	63769.0	0.187
Baseball Diamond	64182.5	0.434	63279.0	0.272
Basketball Court	65015.5	0.548	65977.0	0.793
Community Centre	62340.5	0.120	62594.5	0.131
Football Field	62936.0	0.051	64990.5	0.343
Gardens	62970.5	0.116	65939.0	0.758
Off-Leash Dog Park	63446.0	**0.035**	64855.0	0.228
Outdoor Rink	65333.0	0.298	65582.5	0.374
Playground	66209.5	0.906	60761.0	**0.042**
Pool	65498.5	0.648	64064.0	0.228
Skateboard Park	65787.5	0.676	62628.0	**0.026**
Soccer Field	66366.0	0.949	64955.5	0.592

Spraypad	62842.0	0.168	61624.5	**0.048**
Swingset	63618.5	0.320	59326.5	**0.011**
Tennis Court	65419.0	0.690	60552.0	**0.020**

significance at p < .05 is bolded

Mother's education level is not associated with proportions of free time spent in different recreation types on weekdays after school, off-leash dog parks being the only exception. On weekends, participants with mothers who have not graduated college or university spent significantly less proportion of their free time in parks with typical amenities or courts (i.e. playgrounds, swingsets, tennis courts).

Table 4.14 – Mann-Whitney tests for father's education level differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is Did not graduate college or university.

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	77338.0	0.598	76656.5	0.389
Baseball Diamond	69929.5	**0.008**	70672.0	**0.014**
Basketball Court	76533.5	0.452	74853.0	0.116
Community Centre	76430.0	0.454	72166.0	**0.023**
Football Field	73887.0	**0.018**	75438.0	0.076
Gardens	76674.0	0.429	77200.5	0.511
Off-Leash Dog Park	76088.0	0.112	76483.0	0.161
Outdoor Rink	78563.0	0.953	78115.5	0.662
Playground	77741.0	0.782	70530.0	**0.009**
Pool	76773.0	0.461	74015.0	**0.040**
Skateboard Park	78185.5	0.822	75925.0	0.159
Soccer Field	66119.5	**0.000**	69077.5	**0.003**
Spraypad	77078.0	0.595	73329.5	**0.050**
Swingset	76540.0	0.514	70514.0	**0.008**
Tennis Court	74165.0	0.150	71693.5	**0.014**

significance at p < .05 is bolded

Father's education level has large percentage differences in weekday proportions of exposure to the two most numerous amenities, baseball diamonds and soccer fields. Participants with fathers who have not graduated college or university spent significantly less of their proportion of free time in those two amenities. On weekends, the differences are lower, though still significant and present among other recreation types. Significant engagement differences for parks with a typical set of structures (e.g. playgrounds, tennis courts, spraypads, swingsets) appear on weekends, where participants whose fathers have not graduated college or university spent significantly less proportion of their free time in those types. This weekend effect of engagement with parks with a typical set of structures was also present in mother's education level (table 4.13).

Table 4.15 – Mann-Whitney tests for urbanicity differences in proportions of free time spent in fifteen recreation types, per day type. Reference group is urban/suburban.

Recreation Type	**Weekdays**		**Weekends**	
	U	p-value	U	p-value
Arena	64391.0	**0.000**	65707.5	**0.000**
Baseball Diamond	18896.0	**0.000**	32586.5	**0.000**
Basketball Court	49944.0	**0.000**	59097.0	**0.000**
Community Centre	55215.5	**0.000**	56154.5	**0.000**
Football Field	70113.0	**0.000**	72822.0	**0.000**
Gardens	61519.0	**0.000**	67691.5	**0.000**
Off-Leash Dog Park	76001.0	**0.005**	74632.0	**0.000**
Outdoor Rink	78957.0	0.233	77206.0	**0.006**
Playground	30581.5	**0.000**	41211.5	**0.000**
Pool	58915.0	**0.000**	63467.0	**0.000**
Skateboard Park	69508.5	**0.000**	70827.5	**0.000**
Soccer Field	22336.5	**0.000**	37207.0	**0.000**
Spraypad	50569.0	**0.000**	56928.0	**0.000**
Swingset	35027.5	**0.000**	44168.0	**0.000**
Tennis Court	41897.5	**0.000**	50134.0	**0.000**

significance at $p < .05$ is bolded

Statistically significant differences in proportions of free time spent in the fifteen recreation types is present for all park and recreation types when comparing urban/suburban with small town/rural urbanicities. The percentage differences between urban/suburban and small town/rural follow a collinear pattern with the differences in count of recreation amenities per type. This means that, as the count of a recreation type increases, the percentage difference in engagement increases in parallel. Consistently, participants living in rural or small town locations spent significantly less proportion of free time in all fifteen recreation types.

4.5 Individual, Interpersonal, Social, and Built Environment Factors

The fourth research question, "What individual, interpersonal, and built environment factors are associated with free time spent on (a) weekdays and (b) weekends in parks and recreation spaces?", is the ultimate question in this thesis, one that builds upon the results of the first three research questions. To determine which socio-ecological factors can influence free time in parks and recreation spaces, a multiple linear regression was performed. A breakdown of the blocking of these variables can be seen in figure 4.1. The multiple regression was run to examine the relationships of independent variables with a participant's proportion of free time in parks and recreation spaces. Separate regressions were performed on both the weekday free-time and weekend free-time proportions.

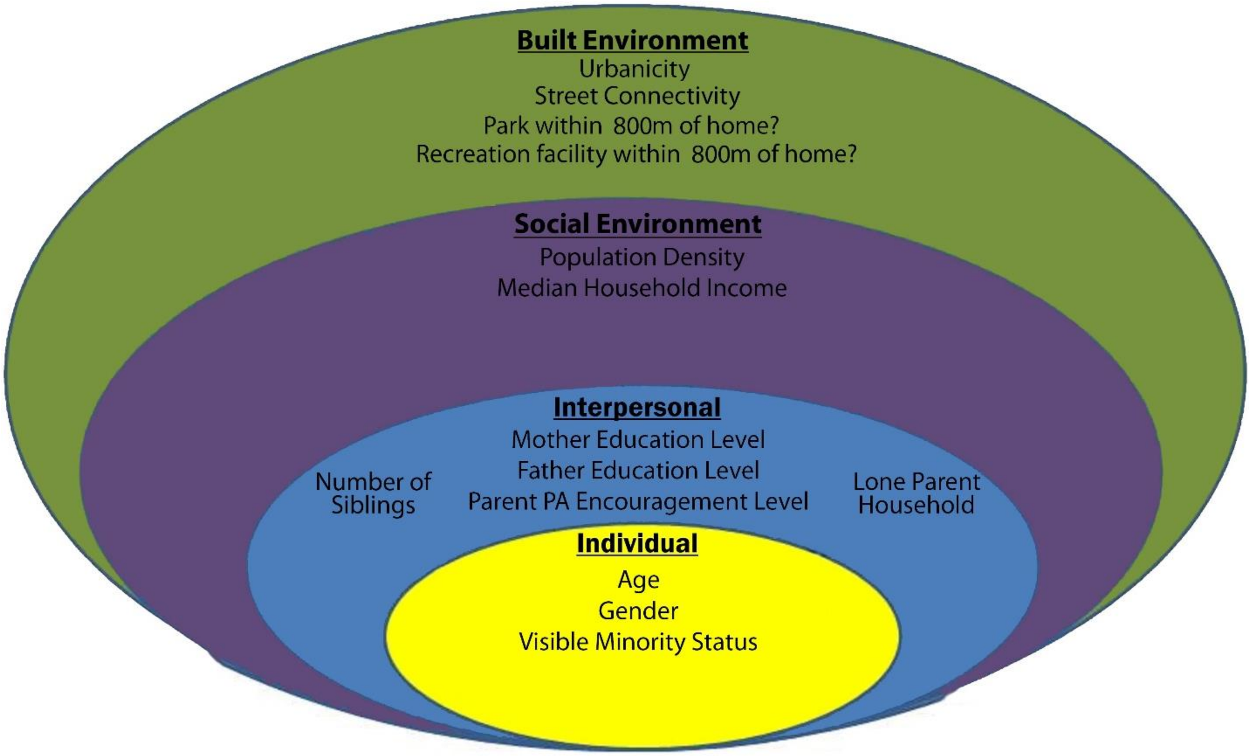

Figure 4.1 – Modified Socio-Ecological model (SEM) with independent variables used in hierarchical blocks for multiple linear regression. The levels Individual, Interpersonal, Social Environment, and Built Environment represent successively-included blocks of variables used in modelling.

Tables 4.16 and 4.17 below show model results, including coefficients, R and R^2, and changes between models when adding successive blocks of independent variables. For weekdays: independent SEM variables were associated with 10.4% of the variance in proportion of free time spent in parks and recreation spaces, $F(19, 828) = 7.780$, $p < .001$, $R^2 = .104$, with seven variables being statistically significant ($p < .05$) in the fourth model. For weekends: independent SEM variables were associated with 15.9% of the variance in proportion of free time spent in parks and recreation spaces, $F(19, 828) = 14.949$, $p < .001$, $R^2 = .159$, with five variables adding statistically significantly to prediction ($p < .05$) in the fourth model.

Table 4.16 – Summary of multiple linear regression for variables associated with free time spent in parks and recreation spaces on weekdays (n = 848).

Independent Variable (reference group)	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	B	SE B	β	B	SE B	β	B	SE B	β	B	SE B	β
Age	-1.59	1.51	-3.63	-1.59	1.51	-3.54	-1.39	1.51	-3.25	-1.49	1.41	-3.54
Gender (female)	4.29	2.63	5.65	4.29	2.63	5.65	4.29	2.63	5.55	3.04	2.63	4.08
Visible Minority Status (no)	-9.43	3.05	-10.60**	-8.70	3.04	-9.79**	-8.52	3.15	-9.52**	-6.76	3.15	-7.50*
Mother's Education Level (graduated college/university)				6.40	3.56	7.25	5.97	3.56	6.72	5.97	3.46	6.72*
Father's Education Level (graduated high school)				9.09	3.15	10.52**	8.98	3.15	10.41**	6.40	3.15	7.36*
Parent PA Encouragement (weak)				-18.94	9.64	-7.69*	-18.94	9.64	-7.69*	-15.63	9.42	-6.20*
Lone Parent Household (no)				1.61	3.15	1.82	1.61	3.25	1.71	1.61	3.15	1.71
Number of Siblings				1.71	1.11	5.34	1.71	1.11	5.44	1.51	1.11	4.81
DA Population Density							<0.01	<0.01	-4.21	<0.01	<0.01	-3.63
DA Median Household Income							<0.01	<0.01	-1.69	<0.01	<0.01	3.15
Urbanicity (urban/suburban)										20.68	4.39	19.72**
Street Connectivity										0.50	0.10	19.84**

Park within 800m Euclidean buffer (no)										9.42	4.19	8.22**
Recreation Facility within 800m Euclidean buffer (no)										8.33	2.74	11.07**
R		.132			.209			.212			.323	
R^2		.017			.044			.045			.104	
F for change in R^2		4.990**			3.264**			0.672			7.780**	

Model 1 = Individual
Model 2 = Individual + Interpersonal
Model 3 = Individual + Interpersonal + Social Environment
Model 4 = Individual + Interpersonal + Social Environment + Built Environment
Note: due to log transformation of outcome variable, coefficients were exponentiated
*p < .05, **p < .01.

Table 4.17 – Summary of multiple linear regression for variables predicting free time spent in parks and recreation spaces on weekends (n = 848).

Independent Variable (reference group)	Model 1			Model 2			Model 3			Model 4		
	B	SE B	β	B	SE B	β	B	SE B	β	B	SE B	β
Age	-2.76	1.41	-6.48*	-2.76	1.41	-6.39*	-2.37	1.41	-5.54	-1.98	1.41	-4.59
Gender (female)	7.47	2.53	10.07**	7.47	2.53	10.19**	7.25	2.53	9.75**	5.87	2.43	8.00*
Visible Minority Status (no)	-9.43	2.94	-10.77**	-8.70	3.05	-9.97**	-7.78	3.05	-8.88**	-4.50	2.94	-5.16

Mother's Education Level (graduated college/university)		4.81	3.46	5.55	3.46	3.46	4.08	4.92	3.36	5.65
Father's Education Level (graduated high school)		3.67	5.76	2.43	4.29	3.05	5.13	3.15	5.44	2.12
Parent PA Encouragement (weak)		-6.29	9.42	-2.47	-6.29	9.31	-2.47	-3.82	8.87	-1.49
Lone Parent Household (no)		5.55	3.05	6.29	5.13	3.15	5.76	5.87	2.94	6.61*
Number of Siblings		0.40	1.11	1.31	0.60	1.11	1.82	0.20	1.01	0.70
DA Population Density					<0.01	<0.01	-12.45**	<0.01	<0.01	-8.06*
DA Median Household Income					<0.01	<0.01	-3.44	<0.01	<0.01	1.61
Urbanicity (urban/suburban)								32.98	4.08	32.18**
Street Connectivity								0.80	0.10	33.51**
Park within 800m Euclidean buffer (no)								1.92	3.87	1.71
Recreation Facility within 800m Euclidean buffer (no)								2.63	2.63	3.56
R	.167		.197			.231			.399	
R^2	.028		.039			.053			.159	
F for change in R^2	8.118**		1.323**			6.394			14.949**	

Model 1 = Individual
Model 2 = Individual + Interpersonal

Model 3 = Individual + Interpersonal + Social Environment
Model 4 = Individual + Interpersonal + Social Environment + Built Environment
Note: due to log transformation of outcome variable, coefficients were exponentiated
*p < .05, **p < .01.

There are some notable differences in findings among the two models from the different day types. Among both models, when successively adding variables from the higher levels of the SEM, R^2 improves. The inclusion of population density and median household income from the Social Environment level of the SEM does not significantly improve model fit. The weekend model explains more of the variance (16%) of the outcome variable than does the weekday model (10%). The R value for the fully-adjusted weekend model (.399) also denotes a better model fit than the fully-adjusted weekday model R value (.323). On the other hand, the weekday model has more predictor variables (7 variables at $p < .05$) that significantly influence the outcome variable than does the weekend model (5 variables at $p < .05$).

In terms of the independent variables and their coefficients, there are contrasts with the same variable when moving between successive models and between day types. Visible minority status has a significant influence on free time in parks and recreation spaces on both day types, but not in the fully-adjusted weekend model that includes built environment variables. A participant's father's education level (i.e. whether dad graduated from high school) and mother's education level (i.e. whether mom graduated from college or university) has significant influence on weekday time spent, but not on weekend time spent. When encouragement from parents for physical activity is weak, there exists the same day-type dichotomy. In the fully-adjusted models where the built environment variables enter the mix, they all have significant influence on time spent, except for having a park or recreation facility within 800m of participant homes on weekends.

Coefficients from independent variables in the models can be looked at in terms of how much they effect the amount of the outcome variable, all other variables held constant. Regarding weekday model 1 (Individual variables), a participant identifying as visible minority results in a 9.4% decrease in proportion of free time in parks and recreation spaces. Models 2 (Individual + Interpersonal variables), 3 (Individual + Interpersonal + Social Environment variables), and 4 (Individual + Interpersonal + Social Environment + Built Environment variables) see slight differences in decreasing proportions of free time spent among participants identifying as a visible minority, with 8.7% for model 2, 8.5% for model 3, and 6.8% for model 4 respectively. Father's education level is also associated with significant increases in proportion of free time in parks and recreation spaces on weekdays. This association is consistent across models 2, 3, and

4, with 9.1%, 9.0%, and 6.4% respective increases in proportion of free time spent. When parents confer only weak encouragement for physical activity, there are large significant decreases in proportion of free time in parks and recreation spaces on weekdays, in the range of 16-19% across models 2-4. This drastic decrease highlights how critical parental emphasis of physical activities can drive exposure to physical activity locales such as parks and recreation spaces.

When the built environment variables are included in modelling of the weekday proportion of free time in parks and recreation spaces, they all play a significant role, but to varying degrees. Increasing street connectivity (i.e. greater number of intersections near a participant's home) results in a 0.5% increase in outcome proportion, and having a park within 800m of a participant's home results in a 9.4% increase in outcome proportion. Having a recreation facility within 800m distance of a participant's home results in an 8.3% decrease in outcome proportion.

Moving onto the weekend models, the association for visible minority status remains similar to the weekday model (< 1% difference), as do the associations among the built environment variables. The only exception is having a park or recreation space within 800m of home becomes non-significant on the weekends, possibly signifying broader mobility patterns on weekends among STEAM participants and their parents/guardians. Having two or more parents is significant only on weekends and only in the fully-adjusted model, and results in an increase proportion of free time in parks and recreation of 5.9%.

The most compelling difference between the weekday models and the weekend models are seen among age and gender. For age, in weekend models 1 and 2, an increase of one year results in a decrease of 2.7% of proportion of free time in parks and recreation spaces. This association with age is not significant in weekend models 3 and 4, when social and built environment variables are added. Gender, however, has significant associations with proportion of free time in parks and recreation spaces across all weekend models, with males showing a 7.5% increase in outcome proportion in the first two models, a 7.3% increase in the third model, and a 5.9% increase in the fully-adjusted model. This shows a potential gendered approach to emphasizing and/or permitting exposure to parks and recreation spaces. Such a significant finding, along with the others mentioned, will be discussed in the next chapter.

5 Discussion and Conclusion

5.1 Summary of Research

Altogether, the research presented in this thesis has illuminated many factors critical to children's health geographies. Broadly speaking, the research uncovered children's levels of interaction with parts of their environments. More specifically, this thesis used novel techniques to generate objective measures of where and when children spend their free time exposed to or engaged in recreation, and to identify how characteristics of children (e.g., age, gender, visible minority status) may influence such free-time exposure/engagement. Secondarily, this thesis examined how different methods for measuring children's levels of interactions with parks and recreation spaces can lead to disparate results. It is critical to interrogate common methods used, as some of these methods have been used as frameworks for policies steering how parks and recreation spaces are both provisioned and justified to the public (City of London, 2019). In this thesis, four interconnected research questions placed scrutiny on certain measurement methods and their applicability to populations of children ages 9-14. These four research questions untangled how measurement disparities may affect provisions and justifications for parks and recreation spaces. Because it is critically important to understand the population being affected by such policies, this research also delved into characteristics of a large sample of children for whom such policies are intended to serve.

To answer the research questions, this thesis processed and analyzed GPS-logger and survey-response data collected from the STEAM project, alongside the inclusion of GIS and census datasets. Bivariate analyses and multiple linear regression comprised the set of analytical mechanisms providing statistical results for each of the research questions. The statistical results were outlined in detail in chapter 4. The intent of this concluding chapter is to summarize the key findings, provide evidence-based interpretations of results, and juxtapose with similar or dissimilar scholarly findings.

5.2 Children's Accessibility, Exposure, and Engagement to Parks and Recreation Spaces

5.2.1 Examination of findings on Accessibility

The first research question, “*How accessible are parks and recreation spaces to children?*”, centered on examining differences in measuring accessibility of parks and recreation spaces from participants’ homes. The accessibility of parks and recreation spaces were contrasted with the priority they are placed in the City of London Parks and Recreation Master Plan (City of London, 2019). Statistical results revealed several compelling findings. In terms of percentage of participant homes in range of parks and recreation spaces, playground structures (e.g. playgrounds, swingsets) and sports fields (e.g. baseball and soccer) are the most easily accessible of the recreation types. Indoor facilities such as arenas, community centres, and pools are the next most accessible. Specialty recreation types which have the least amount throughout London, such as dog parks, gardens, skateboard parks, and outdoor rinks, are the least accessible.

In their systematic review into public open spaces connected to adolescent activities, similar findings regarding types of recreation and their local/regional coverage were discovered by Van Hecke et al. (2018). The majority of papers included in Van Hecke et al’s review uncovered areal coverage of specific recreation spaces accessible to adolescents that are similar to London, particularly in urban/suburban areas of the Global North. Gilliland et al. (2006) used GIS to map out recreation facilities at the level of planning districts throughout London, Ontario. The authors found that, based on the districts, there was a statistically non-significant difference in the provision of multiple types of recreation amenities. However, the authors in that case did not measure accessibility in any greater detail than using entire districts as containers, whereas the research in this thesis measured accessibility using both Euclidean and network buffers to fifteen types of recreation amenities in London. Thusly, accessibility differs depending on the method of measurement used (i.e. buffer type).

When analyzing differences between two common proximity measurement types, Euclidean buffers and network buffers, average distances from participant homes (n = 586) to nearest recreation amenities and facilities were almost unanimously significantly different. Only one (outdoor rinks) out of fifteen recreation types was statistically non-significant in average distance between Euclidean buffers and network buffers. These findings regarding differences due to buffering methods are consistent with previous studies examined or systematically reviewed in chapter 2. Moreover, these findings are important because many public health researchers whose research objectives include objectively gauging locations children are exposed to, incorrectly rely on expedient proximity-based methods like Euclidean buffers as a proxy for exposures (Kwan et al., 2018; Sadler & Gilliland, 2015; Wang et al., 2018).

Other research has used proximity of a child's home to the nearest recreation amenity as a variable used in analysis (e.g. control, mediator, outcome). For instance, Dunton et al. (2014) found that distance to parks was a significant predictor of park use by children, at all levels of their multilevel models. When examining park use tied to physical activity levels, Mitchell et al. (2016) found that proximity to parks, as measured via Euclidean buffers, significantly influences physical activity patterns of children at differing amounts, depending on the demographic characteristics of the children. Where a big difference lies in the literature is in how researchers utilize different measures of the built environment. Dunton et al. (2014) incorporated variables operationalizing parks, forests, and NDVI greenness, while Mitchell et al. (2016) incorporated variables operationalizing parks with specific amenities, land use mix, and counts of intersections within chosen Euclidean buffer distances. Examining these differences is important because, through multiple linear regression analysis (as seen in tables 4.16 and 4.17), this thesis found that a set of built environment variables had a consistently significant influence on children's free time in parks and recreation spaces. Therefore, how researchers scale and operationalize built environment variables can lead to different results in analysis, and thus different conclusions regarding their influence.

Parks and recreation spaces are known to be spaces with an enormous potential to improve numerous health outcomes in children (Das et al., 2017; Van Hecke et al., 2018), but first the spaces must be accessible to children. Different types of parks and recreation amenities can result in different health outcomes (McGrath et al., 2015; Pearson et al., 2017), yet collectively play a part in the overall physical, social, and mental health of children (Maddison et al., 2010; Mitchell, 2016; Krenn et al., 2011; Pearson et al., 2017; Wray et al., 2020; Yip et al., 2016; Brussoni et al., 2017; Tillmann et al., 2018; Wu et al., 2011). Children have less independent mobility than other age groups, thus proximity measured via buffers is a key measure of accessibility, though the application of buffers in analysis needs be analyzed for statistical sensitivity of the specific buffers used (Mitchell et al., 2016; Amoly et al., 2015; Kwan, 2012). Furthermore, it is critically important for those in charge of managing and provisioning parks and recreation spaces to ensure easy access to them for children of all walks of life. This is because, for instance, children living in households of a lower socioeconomic status, or children living along the urban-rural fringe, have reduced mobility options due to the cost barrier of vehicles and of longer travel distances (Meyer et al., 2016; Clark et al., 2018; Molnar et al., 2004). Therefore, findings in this thesis on the accessibility of parks and recreation spaces among STEAM participant children adds to children's geographies scholarship by showing how different types of spaces have different amounts of accessibility, and that the amounts do not necessarily match with an official city plan that aims for universal accessibility among children.

5.2.2 Examination of findings on Exposure

Accessibility does not consider children's objectively-measured exposures to parks and recreation spaces. That is where GPS data comes in by providing location data that answers this thesis' second research question, "*What proportion of children are exposed to different parks and recreation spaces during their free time on a) weekdays and b) weekends?*".

Determining proportions of exposure depends on using GPS to objectively locate children in parks and recreation spaces. In terms of percentages, proportions of exposed participants follow a similar trajectory to the findings regarding accessibility in the first research question. This means that, for the most numerous and most easily accessible recreation types (i.e. park structures and sports fields), exposure percentages are highest, followed by indoor recreation facilities (arenas, community centres, pools), and concluding with the smallest percentage exposures among the specialty recreation types (dog parks, outdoor rinks, skateboard parks).

As measured via Chi Squared tests for all recreation types, there were significant differences between the City of London policy's service area buffers and GPS-derived participant exposures. These differences signify that using buffers as a proxy for estimating how many children are "served" a recreation amenity based on their home locations (i.e. expected counts), does not match with actual use of amenities (i.e. observed counts), regardless of the type of day. Additionally, percentages of participants exposed to the recreation types is universally less on weekends than on weekdays after school. This day-type dichotomy in exposure may signify more exposure to a variety of land use classes on weekends compared to weekdays, something that Maddison et al. (2010) found in their research into children's free-time environments as well. Children are using park space less on weekends, but parks are nonetheless a considerable investment for local governments. As Horton & Kraftl suggest (2018), and the ParticipACTION reports emphasizes (2020), consistently providing people information regarding the potential health benefits for children when they are exposed to play in parks and recreation spaces can foster increased exposure and engagement in the spaces. To increase engagement in parks and recreation spaces, Das et al. (2017) suggest the need to remove socioeconomic, cultural, and physical barriers. Brussoni et al. (2020), emphasizing how outdoor play spaces are important for promoting children's well-being and development, suggest allowing children greater independence during their free time by both limiting parentally-organized activities and ensuring safety in local parks and recreation spaces.

Research into exposures to specific types of parks and recreation spaces is sparse, hence the novel aspect of this thesis' research. However, some interesting findings among the literature relate to children's exposures to parks and recreation spaces and this thesis' second research question. In their study involving Scottish children, Olsen et al. (2019) found that children often used specific recreation amenities outside their home neighbourhood, even if the specific amenities were also available close to home; their finding denotes the need to accurately measure exposure to uncover levels of interactions with specific spaces. Utilizing both quantitative and qualitative measures of children's spatial exposures, Loebach & Gilliland (2016) found that children habitually spend very small proportions of their free time playing outdoors in their immediate neighbourhoods. Jones et al. (2009) found that children's bout-based activities were significantly located in neighbourhood parks and recreation spaces, but sustained activities were located further afield. Pertaining to day-type differences in exposures to parks and recreation spaces, Maddison et al. (2010) found that children's activity patterns were more disparate (i.e. less clustered in times and spaces) on weekends compared to weekdays, which is similar to the findings answering the second research question of this thesis.

Furthermore, numerous research projects in children's health geographies have utilized GPS data to examine differences between accessibility and exposure. Ward et al. (2016) found significant differences in measuring New Zealand children's GPS exposures to greenspaces and municipal parks versus the proximity of such places to their home and school locations. Upon examining findings from a sample of rural children in northwest Ontario, Schieman (2018) found significant differences between GPS exposures and GIS-measured proximities to a set of spatial types (commercial, industrial, institutional, residential, water). When examining youth activity patterns in Halifax, Katapally et al. (2016) discovered large differences in locations youth utilize for physical activity when contrasted with the recreation amenities nearest to their home and school; the differences Katapally et al discovered varied from weekdays to weekends.

These findings, alongside the findings in this thesis' research, collectively relate to exposure measurements uncovering disparate uses of parks and recreation spaces across types of spaces and periods of free time. Together they denote the importance of knowing what types of parks and recreation spaces are used, and whether they are used more on weekdays or weekends. Precisely understanding what types of parks and recreation spaces are utilized during children's free time will aid in developing programming for such spaces (Thompson et al., 2014; Clark et al., 2019; Sibbald et al., 2017). For instance, Thompson et al. (2014), through an analysis of stakeholder engagement mechanisms (online courses, public lectures, workshops) across multiple Australian locations, found that such mechanisms aided in uncovering both the frequency of use and the opinions of public recreation spaces by various groups, including children. Within Canada, Clark et al. (2019) found variability in the no-charge use of recreation spaces among grade 5 students living in London, Ontario. The variability in use among the grade 5 students was most significantly seen in an urban/suburban dichotomy, as well as variability in use among genders and among household income categories. Methodologically, this thesis' research shows how robust an official parks and recreation policy is at addressing provision of spaces, particularly because the policy includes spatial components (City of London, 2019). Matching such policy-based spatial components to GPS-derived observations is a strength of this thesis' research.

5.2.3 Examination of findings on Engagement

5.2.3.1 Time in Parks and Recreation Spaces

GPS exposure data can be further contextualized by incorporating a time element into the data. This additional element enhances exposure, turning it into time-weighted engagement. Engagement has been operationalized in the literature in many ways, including the synchronization of physical activity measures with GPS-derived locations, ecological momentary smartphone assessments (EMA) containing geolocations, and applying the amount of GPS data (e.g. number of points per epoch) into a spatial bin (Chaix, 2018; Loveday et al., 2015; Shmool et al., 2018). This thesis' research utilized the latter by intersecting the one-second-epoch GPS logger points with the hexagon spatial bin (refer to section 3.3.1), thus providing time weights to each hexagon bin. Processing the data this way provided answers to the third research question, "*How much free time do children spend in parks and recreation spaces on (a) weekdays and (b) weekends?*". Specifically, tables 4.8 and 4.9 in chapter 4 help answer the question by providing descriptive statistics and groups differences of proportions of participant engagement within fifteen recreation types, per day type.

As identified in chapter 4, overall engagement of STEAM participants in parks and recreation spaces during free time is low when compared to engagement in other land use categories (e.g. commercial, institutional, residential), regardless of day type. Residential and institutional land uses dominate children's proportions of free time, relegating parks and recreation to third or fourth greatest proportion. This finding is consistent with literature that has uncovered trends showing increasing sedentary behavior and screen time among children, as well as increasing structured activities occurring indoors. These behaviors predominantly take place in residential and institutional spaces (see section 2.1).

Delving into STEAM participant engagement within parks and recreation spaces, there were interesting findings when contrasting dichotomous groups of children and their proportions of free time in such spaces. Although percentage differences were small, there were significant differences between males and females in their engagement within park-based amenities. For instance, regardless of day type and where parks had a typical set of structures (e.g. playground, swingsets, tennis courts, gardens), males spent a significantly greater proportion of their free time in them (as seen in tables 4.9 and 4.10). A comparable group difference was seen for community centres. This finding aligns with existing literature, which has mostly attributed more time spent in recreation spaces to males instead of females (Matz et al., 2014; Molnar et al., 2004; Tester & Baker, 2009), often due to the greater level of independence granted to males at an earlier age (Loebach & Gilliland, 2019). Indeed, multiple linear regression results of free time spent in parks and recreation spaces suggest that total overall proportion in all recreation types is greater for boys (see tables 4.16 and 4.17).

When examining visible minority status, larger percentage differences were seen. STEAM participants not identifying as visible minority (i.e. Caucasian) spent a significantly smaller proportion of their free time in field sports locations such as baseball diamonds and soccer fields.

Smaller percentage differences were also evident on weekends for recreation facilities such as pools and community centres. What have others found pertaining to ethnic disparities? Marquet et al. (2019) examined park use by ethnic minority children in New York City, and found that frequency, type, and duration of use of parks and recreation spaces varied among different ethnic groups. The authors also found that frequency, type, and duration of use varied between minorities as a whole and the majority ethnic group. Research delving into differences in use of such spaces between ethnicities is scant, thus findings in this thesis are novel and worthy of subsequent research. Researching why spatiotemporal behaviors exists among different ethnicities when exposed to or engaged in parks and recreation spaces is critical, because equity in access and utilization of public spaces by recent immigrants & visible minorities is key to improving overall public health and abating divides in health outcomes (Das et al., 2017). In Canada, declining health outcomes among children leads to increased healthcare costs to society as a whole. How these findings can be applied to policy and programming for minority children is elaborated on in section 5.4.

The educational achievements of parents provided another set of compelling differences among participants that helped to answer the third research question. In particular, and regardless of which parent, participants with a parent that had graduated college or university spent significantly more free time in parks with structures (e.g. playground, swingsets, spraypads, tennis courts), but only on weekends. In the case of their father having graduated college or university, participants spent significantly more free time on sports fields on weekends. Parental education's relation to engagement in parks and recreation amenities was also discovered by Wilk et al. (2018) and Maatta et al. (2018), where they both found parental education's links with household income meant children with highly-educated parents are more likely to spend time in parks and recreation amenities after the end of their parent's work hours or when parents have weekends off. Related to the coupling of education with income, Chaix (2016) discovered a selective daily mobility bias effect, where higher-educated and higher-income families drove out of their neighbourhoods to be exposed to their favorite parks and recreation amenities, and subsequently spent significantly more time in those far-flung parks and recreation destinations. In essence, they were more engaged with their favorite parks and recreation locales, which were not necessarily the ones closest to home. Chaix's findings also relate back to research questions 1 and 2, both of which seek to examine how accessibility from home locations differs from objectively-measured exposure and engagement.

It is important to point out once more that the proportion of STEAM participants' free time in parks and recreation spaces is low overall, a finding which many researchers have identified among Canadian children over the past few decades (Brennan et al., 2014; Prince et al., 2020). Consequently, many children are not benefitting from potentially positive health outcomes (e.g. MVPA, social connectedness, mental health, cognitive acuity) associated with such spaces (Loebach & Gilliland, 2016; Molnar et al., 2004; Tillmann et al., 2018; Timperio et al., 2015; Wood et al., 2013; Wray et al., 2020). Furthermore, it is critical to understand which groups of children are engaged with which types of parks and recreation spaces, and if the proportions of engagement are above or below government health-promotion guidelines or policy expectations (ParticipACTION, 2020; City of London, 2019). As mentioned above for research question 2, determining what types of parks and recreation spaces are used more on weekdays or weekends will aid in developing programming for them (Thompson et al., 2014; Clark et al., 2019; Sibbald et al., 2017). Duration of time, which along with GPS data is this thesis' definition of engagement, provides stronger findings that further justify such programming of parks and recreation spaces.

5.2.3.2 Influence of SEM Factors on Time in Parks and Recreation Spaces

Research question 4 delves into the characteristics of STEAM participant children, and what about those characteristics can influence proportion of free time in parks and recreation spaces. The question asks, "*What are the individual, interpersonal, and built environment factors associated with free time spent on (a) weekdays and (b) weekends in parks and recreation spaces?*" Via multiple linear regression modelling, this thesis examined the level of influence demographic and socioeconomic variables contained in a modified Socio-Ecological (SEM) model (see figure 4.1) have on engagement in parks and recreation spaces. Through successive hierarchical blocks, each level of the SEM added independent variables to model, and the regression measured their influence on proportion of free time in parks and recreation spaces.

Several regression findings were particularly stark. Pertaining to individual-level variables, visible minority status was a key indicator of proportion of free time spent in parks and recreation spaces. On both weekdays and weekends, participants identifying as visible minority spent significantly less free time in parks and recreation spaces. As mentioned previously (Marquet et al., 2019; Woodland, 2008), frequency, type, and duration of use of parks and recreation spaces has been known to vary among different ethnic groups, and between minorities as a whole and the majority ethnic group. Further research into this individual-level phenomenon, which may be related to other factors (e.g. health status, household income, language barriers) is warranted, lest ethnic divides in service provision or engagement with public open spaces increases unchallenged.

Parental education levels influence on engagement in parks and recreation spaces is not consistent across day types. For instance, across all SEM blocks of the models, a higher level of participant father's education is associated with modest increases of proportion of free time (i.e. 7-9%) in parks and recreation spaces on weekdays. However, this influence from father's education level disappears on the weekends. Mother's education level is consistently non-significant in its influence on participant proportion of free time in parks and recreation spaces. This finding regarding maternal education contrasts with similar research. For instance, Button et al. (2020) found associations between mother's education level and physical activity levels of children, though environmental variables were not significant factors in the authors' models. Van Hecke et al. (2016) found a strong positive association between children of highly-educated mothers and their increased use of public open spaces. Those who found influence from father's education level with time spent in parks and recreation spaces discovered different influences, such as Clark et al. (2019) who found children having father's with low educational attainment was related to increased time in specific recreation facilities.

When parental encouragement regarding their child's physical activities was weak, participants' proportion of free time in parks and recreation spaces was significantly reduced, on the order of 18-19% on weekdays after school, across all three models the variable was included in. The reduction in outcome proportion on weekends was less, on the order of 6-7%, and was not statistically significant. Nonetheless, the weekday figures are startling and indicative of the importance of parents/guardians setting an example for children to be engaged in health-promoting venues such as parks and recreation spaces. Physical activity is intertwined with engagement in parks and recreation, as other locations like residences or commercial gyms are considered relatively limited in providing the venue for government-recommended daily activity levels for children (Smith et al., 2019; Van Hecke et al., 2018).

Parental influences on spatial interactions and activities of their children have been previously studied. Of note, Wilk et al. (2018) found that parental support for, and perceptions of, the importance of physical activity influenced transportation to activity venues such as parks and recreation amenities. Veitch et al. (2016), using focus groups and a computer-aided parks and recreation quality-rating application, found that in addition to their own opinions on parks and recreation amenities, children’s perceptions on what their parents thought of the same amenities affected their engagement with them. Taylor et al. (2018) noted how parental support for physical activity is a significant barrier to children’s physical activity levels, and that support or lack thereof extends to the neighbourhood spaces children are permitted to engage in. Such findings are also reflected in Loebach & Gilliland’s (2019) qualitative examination of children’s perceptions and parental support of neighbourhood spaces. This thesis’ findings regarding the significant influence on outcome proportion of weak encouragement from parents adds weight to interpersonal influences on engagement in children’s healthy places.

Urbanicity is a significant factor associated with children’s engagement within parks and recreation spaces. Findings in this thesis support that claim, as STEAM participants living in an urban or suburban residence spent significantly more proportion of free time in all recreation types compared to participants living in a rural or small-town setting, regardless of day type. Even rural/small town participants whose homes were on the edge of London’s suburban region (see figure 1.1) spent significantly less free time in London’s park and recreation amenities. In fully-adjusted models, residing in an urban/suburban region, as contrasted with rural, small town, or urban-rural fringe, plays a key role in all levels of interaction measurements (accessibility, exposure, engagement) that this thesis is concerned with.

Compared to bivariate analyses, fully-adjusted models from multiple linear regressions were no different in uncovering associations between STEAM participants’ urbanicity and their proportion free time in parks and recreation spaces. Alongside urbanicity, street connectivity (i.e. number of intersections within 800m radius of home location) and whether a park or recreation facility was within 800m (Euclidean) of participants’ homes heavily influenced engagement. Regardless of day type, the SEM block of built-environment variables significantly influenced engagement, with the effect being that, on weekdays, increases in all four – more urbanized, more intersections, park present within 800m of home, recreation facility present within 800m of home – resulted in 21%, 1%, 9%, and 8% increases in proportion of free time in parks and recreation spaces respectively (see table 4.16). Weekend values differed for urbanicity's influence, rising from 21% to 33%, as well as for park presence and recreation facility presence within 800m, which fell from 9% to 2%, and 8% to 3% respectively (see table 4.17).

This urban-rural divide in engagement has been uncovered by numerous authors, including Collins et al. (2012) in their project involving GPS logging and physical activity levels of children living in suburban or rural locations of central England. In addition, both Cottrell et al. (2015), with their study of relationships between urbanicity, GPS exposures, and household incomes, and Button et al. (2020), with their findings that contrast rural northwest Ontario participants with urban/suburban southwest Ontario participants, provide findings also demonstrating an urban-rural divide similar to the divide found in this thesis' regression models. Literature on the influence of urbanicity on children's spatial interactions is extensive, though little of it specifically focusses on parks and recreation space engagement as an outcome. Nevertheless, some parallels do exist with this thesis' research. One parallel can be seen in Burgi et al. (2016), in which the authors found children's engagement with public recreation facilities and school recreation facilities varied across different socioeconomic groups; these groups were defined by residence areas and were collinear with an urban/suburban/rural typology. Collins et al. (2012) also found statistically significant differences in physical activity engagement within parks based on an urban-rural stratification of participants.

As evidenced by research employing urbanicity as a factor, the sheer lack of parks and recreation opportunities for rural residents in North America has prompted a call to action by a collaboration of professors (Meyer et al., 2016). The call to action seeks to address the shortcomings of accessibility, exposure, and engagement to various amenities in rural locations, parks and recreation among them. Even though Meyers' research focus is on the United States, both Nykiforuk et al's (2018) and Button et al's (2020) research corroborates similar needs to address shortcomings in rural Canadian locations. The findings in this thesis, which includes the significant influence having a park or recreation facility within 800m of home has on proportion of free time after school in them, add to the weight of evidence pointing to the need to address shortcomings in provisioning parks and recreation spaces in rural locations. When examining accessibility among the edge cases (participants with homes on the urban-rural fringe of London), even though the cases are a small sample of n = 16, they were unanimously underserved accessibility to parks and recreation spaces. The edge cases were thus reflective of Meyer et al's and Nykiforuk et al's findings.

Altogether, the findings in the multiple linear regressions were critical in uncovering the influences participant characteristics have on proportion of free time spent in parks and recreation spaces. As mentioned throughout this thesis, the importance of these findings is centered on the health benefits children can obtain from easy access, modest exposure, and healthy engagement associated with parks and recreation spaces (Das et al., 2017; Van Hecke et al., 2018). Individual and interpersonal characteristics of children are not disconnected from the potential for interactions with their environments, thus this thesis' analysis into their interconnected influences through multiple linear regression of SEM variables contributes to children's health geographies scholarship.

Results presented herein can support future research involving interventions focused on getting children more engaged with parks and recreation spaces. The results can also support policymakers and parks and recreation programmers to better tailor such spaces for engaging under-engaged children who have certain individual or interpersonal characteristics (Greer et al., 2015; Tester & Baker, 2009). This tailoring of spaces can be modified for variability in time (i.e. difference in weekdays versus weekends) to make it truly match with spatiotemporal research. From the research this thesis uncovered regarding varying proportions of free time spent in parks and recreation spaces, the statistical and spatiotemporal influences of SEM factors on specific day types can aid in future methodological considerations for children's accessibility to, exposure to, and engagement with health-benefitting parks and recreation spaces.

5.3 Contributions to Children's Health Geographies Scholarship

The findings uncovered through spatial and statistical analyses in this research will aid in future children's health geography research. Firstly, this thesis highlighted how linking expansive GPS datasets (i.e. billions of recorded points) to fine-resolution, contiguous spatial bins via GIS processing models showcases the ability of modern geography-centric applications to provide research results in a timely fashion. The integration of open-source spatial data, government census data on demographics and socioeconomics, and observation data collected from participants provides a rigorous and flexible framework for linking accessibility, exposure, and engagement factors into analyses done at any spatiotemporal scale.

Moving beyond simple accessibility measures and proxies, and incorporating exposure and engagement data via GPS logging, is a key contribution of this thesis' research. As has been discussed in detail, buffer areas produce significantly different results when compared to exposure areas, which produce significantly different results when compared to time-weighted engagement in those same areas (Mitchell et al., 2016; Schieman, 2018). Using buffers alone to understand children's environments leads to misrepresentation of their activity spaces, in essence the spaces they are objectively exposed to and thus influenced by. This misrepresentation was exemplified in Wang & Kwan (2018), in which the authors dissect spatiotemporal frameworks and how many of them miscalculate exposures of participants to outcome-influencing environments. Smith et al's (2019) systematic review examined how studies that utilize location-technologies-derived activity spaces for their child participants reveal more statistically robust relationships – positive or negative – then when contrasted with Euclidean or network buffers that merely intersect destinations common among child participants.

There is much research in children's geographies that could have benefitted from the application of this thesis' findings regarding accessibility, exposure, and engagement. For instance, Balseviciene et al. (2014), in their study into children's mental health linkages with parks environments and overall residential greenness, could have benefitted from incorporating exposure data from their participants instead of using only buffers originating from participant home and school locations. In their case, acquiring location data from participants and weighting it by time would have strengthened the relationships between parks and greenspace exposures and their mental health outcomes. Markevych et al. (2014), in their study into the effects of a variety of types of greenspaces on children's cognitive outcomes, used only Euclidean buffer measures from homes and schools as proxy for participant interactions with greenspaces. Again, acquiring location data from participants via location technologies like GPS, then additionally weighting the location data by time, would have strengthened the relationships between cognitive outcomes and greenspaces.

Findings in this thesis can be used to inform future research focusing on children and the spaces they interact with. Parks and recreation spaces may have been the focus of this thesis, yet the rich STEAM dataset has numerous other mechanisms that collected qualitative data on participant perceptions, opinions, and health statuses. Bridging the GPS location data analyzed in this thesis with more qualitative focus group or quantitative health-measurement tools could unearth outcomes linking scarcely-researched phenomena together. Potential exists to see whether exposure and/or engagement with parks and recreation spaces has a temporal influence on sleep quality, or sleep duration, or dietary patterns, or all three if utilizing a mixed-effects model.

Findings regarding independent variables analyzed within blocks of the Socio-Ecological model lend weight to evidence of poorly engaged or underserved groups of children. The findings on children identifying as visible minority and their exposures and engagement with parks and recreation spaces underscores how critical it is to expand research on vulnerable segments of the population. Demographic analyses in this thesis also added to the growing literature on gender disparities in exposure and engagement with parks and recreation spaces, where trends show females are less exposed/engaged to parks and recreation spaces, and thus less able to benefit from the numerous health-positive outcomes associated with such spaces. This thesis found a reduced outcome proportion on weekends for females, where they spent significantly less time in parks and recreation spaces throughout Middlesex-London.

Another key finding in this thesis' research involves the intricacies of urbanicity and its associated built-environment variables. Not only did this thesis employ an urbanicity value for participants' home locations, but it also measured the built environment around a participant's neighbourhood by incorporating related variable data. When combined with urbanicity, street connectivity, park presence, and recreation facility presence provided a robust set of variables that captured the built environment's influences on participants' spatial interactions during their quotidian weeks. Urbanicity has been utilized in other children's geographies research to model outcomes. For example, Rainham et al. (2012) utilized an urbanicity variable to determine physical activity patterns of children within spaces of Halifax, Nova Scotia. Taylor et al. (2018) examined the relationship between urbanicity and children's physical activity by using structural equation models. Other research, particularly studies discussed in chapter 2, utilized their own array of the aforementioned built-environment variables. In Bejarano et al's (2019) research, street connectivity had a positive relationship with children's sedentary behavior & screen time. Marquet et al. (2019) discovered park presence within the immediate neighbourhood significantly influenced low-income children's physical activity levels. Clark et al. (2019) studied children given a free recreation pass into local public facilities and found significant relationships between use of facilities and factors like gender, urban-suburban homes, and median household income.

Examining differences in measurements of accessibility, exposure, and engagement among common approaches applied in children's health geographies – and in parks and recreation policies – is a strength of this thesis. Statistical tests showed how simple Euclidean buffers around spaces of interest, in this case parks and recreation amenities, are inaccurately gauging distances, and are not equivalent to the more accurate circulation network of streets, sidewalks, and multiuse paths children must use to navigate to amenities. Public health researchers and local policymakers should abandon using expedient but inaccurate Euclidean buffers, and instead focus on circulation-based network buffers coupled with exposure data acquired from research volunteers from health geography projects akin to STEAM.

5.4 Factoring Research into Policies and Programming

Part of this thesis examined the City of London's Parks and Recreation Master Plan service areas for parks and recreation amenities, and how the plan utilized Euclidean buffers of varying sizes as a means to define how the city would serve its residents – particularly children – with those amenities. The findings in this research, however, reveal children are not necessarily going to the parks and recreation amenities closest to their home. Tremendous variability was found in the sizes and ranges of participants' activity spaces, and when relating their GPS exposures to buffer measures of accessibility near homes. Thus simply having a park or recreation amenity present within policy service-area distances from homes is not a sufficient measurement for confirming that spaces are provisioned for children. Rather, what is important is having a quality park that children perceive as accessible, safe, and filled of amenities they want to use (Das et al., 2017; Loebach & Gilliland, 2019). This importance is especially critical in low-income neighbourhoods where parents/guardians are not able to drive their kids to the parks and recreation spaces they prefer, and which contain their favorite amenities. This divide in mobility options could undermine the health of vulnerable children (Das et al., 2017; Greer et al., 2015).

Methodologically, research questions 1 through 3 highlighted how inaccurate buffer measurements used are when contrasted with a sample of children's GPS exposures to such spaces. Thus, in regard to policymaking, this thesis' research can play a role in providing mechanisms for more objective measures of accessibility, exposure, and engagement to parks and recreation spaces. Indeed, it behooves policymakers that shape such spaces through their policies to go beyond expedient measures. Simple measures may look good on maps and look as if they provide extensive coverage via the strategic placement of parks and recreation amenities. However, using a less accurate form of measurement (e.g. Euclidean buffers) does not capture the reality of navigation limitations through a city, nor does it truly match with time-space paths that children with different attributes and life situations engage in throughout a typical week.

Policymakers can utilize the findings of this thesis to reformulate their definitions of service areas. Upgrading to buffers derived from a circulation network dataset plus acquiring information of children's contextualized engagement with parks and recreation spaces (e.g. activity diaries) can be combined with location data from representative samples to provide a more thorough idea of what the population being served parks and recreation spaces is objectively doing with the spaces. Thesis research approach can also aid policymakers in isolating which subgroups of children are underserved by the current configuration of parks and recreation spaces. Indeed, findings in this thesis regarding exposure and engagement to parks and recreation spaces by visible minority children, and children residing in rural or small town locations, independent of accessibility, can be seen as a call to action much like Nykiforuk et al's (2018). For instance, programming could be developed in multiple languages that informs ethnocultural minority populations of the parks and recreation amenities available in their neighbourhood (Wray et al., 2020; Tester & Baker, 2009; Veitch et al., 2012). Better serving children living in rural/small town locations is a more complicated endeavor, likely requiring construction of amenities, or a form of rapid low-cost transportation that can make it easy for rural children to transit from the edges of the city to nearby agglomerations of parks and recreation facilities (Meyer et al., 2016; Collins et al., 2012).

Perceptions of the quality of available recreation amenities in the neighbourhood is just as, if not more, important than simple presence in the neighbourhood (Schoeppe et al., 2016; Taylor et al., 2018; Wilk et al., 2018). As described in this thesis and incorporated in analysis models, perceptions of both the availability of amenities and support from parents/guardians to venture into and engage with the amenities, is a key driver in achieving better health among children. As noted by both Wilk et al. (2018) and Smith et al. (2015), parental support follows from parental perceptions of the quality and safety of neighbourhood parks and recreation spaces. Moreover, walkability measures (i.e. street connectivity) play a role in aiding safe navigation to parks and recreation spaces, whilst simultaneously promoting active travel, a practice noted by many researchers as an easy way for children to meet government physical activity guidelines (Buttazzoni et al., 2018; Williams et al., 2018).

The importance of parks and recreation spaces to enable effortless exposure to and engagement with health improvement opportunities is more appropriate in recent years than it has ever been. With rising epidemics of childhood obesity and sedentary behaviors (Brennan et al., 2014; Gilliland et al., 2012; Prince et al., 2019; Grewal, 2013), relying on clinical settings and *ex post facto* interventions to mitigate health problems can adversely impact the health outcomes of this segment of the population throughout the course of their lives. It is in parks and recreation amenities that health-improving behaviors can be easily realized, behaviors that often carry forward from one's formative childhood years into adulthood (Collins et al., 2012; Fitch et al., 2018). The research presented in this thesis highlights how accessibility to health-improving spaces can be more accurately measured, where the measurements can be better applied, and what subsets of children the measurements and associated information should be targeted to. An example of such an effort can be found in Clark et al. (2019), who examined the utilization of a free recreation-facility pass for Grade 5 children and showcased how a wide array of children can benefit from easier access to health-improving spaces. Another instance of a targeted intervention can be seen in Brussoni et al's (2017) research into incentivizing nature and risky play among children by modifying play environments through a systematic design philosophy.

5.5 Limitations of Research

There are several limitations in this thesis research, stemming from both the STEAM project design and the data which was collected and processed. Most pointedly, this thesis did not utilize information regarding the purposes of exposures to parks and recreation spaces, which may have contextualized engagement. Basically, this thesis does not examine how participants are using the spaces they interact with, such as parks and recreation facilities. For example, a participant's twenty-minute exposure to a playground may have involved sitting down and watching their sibling playing and running around while they converse with family or peers. In such an example, no physical activity outcomes were improved, though social and mental health outcomes may have improved. Data from daily activity diaries could have supplied thematic information regarding purposes of children's exposures to parks and recreation amenities, in which quantifiable themes may have been developed for inclusion in statistical analyses. Thus engagement in this thesis is defined by non-contextual exposures weighted by time.

Previous research has shown that when recruiting participants through schools, self-selection bias among participants skews towards those of higher household incomes, those with more free time, those not home schooled, and those with outgoing personalities (Toumbourou et al., 2007). In order to improve on the potential representativeness of the STEAM sample with the sociodemographic profile of children in the study region, a cross-section of elementary and secondary schools stratified by urbanicity and school catchment-area socioeconomic status was applied in the STEAM participant recruitment strategy. Even given the willingness of children to participate in the project, protocol non-adherence from participants, particularly regarding continuity of GPS logging and maintaining device charge, resulted in some inconsistent datasets and the need to invalidate certain participants. Fortunately, invalid participants were not statistically significantly clustered in any schools, urbanicities, or demographic variables.

Location and activity data collection via GPS loggers and diaries provided a snapshot of only two weeks, and across only two seasons. No summer or winter location or activity data was recorded from participants. Summers and winters are known to heavily skew exposures to certain spaces. Winter, for example, is known for increases in proportions of time in indoor spaces such as residential spaces and commercial spaces, and for decreases in proportions of time in recreation and greenspaces (Brum-Bastos et al., 2018; Button et al., 2020; Tucker et al., 2009); this effect is commonly referred to as seasonality. Likewise, and even though it can play a significant factor when analyzing the dichotomy between indoor and outdoor recreation opportunities and usage (Button et al., 2020; Clark et al., 2014; Katapally et al., 2016), daily weather and its effects on children's presence in parks and recreation spaces was not included in analysis. When it comes to daily weather, snow is particularly interesting, as it may provide an environmental situation that objectively increases exposure/engagement to outdoor parks and recreation spaces (Button, 2020; Lewis et al., 2016).

There are also spatial and temporal limitations in this thesis research. The physical environment (built and natural) in parks and recreation spaces is under constant development and maintenance, with an impetus to improve quality and accessibility to such spaces. In terms of measuring engagement throughout the entire study area, the research herein looked at parks and recreation amenities available as of 2019 and compared them to participant exposures and engagements from 2013 at the latest, thus a temporal gap exists. Nevertheless, a thorough visual examination of satellite images of southwest Ontario from 2012 - 2019, plus archived OpenStreetMap layers that included parks and recreation amenities, revealed minor changes in the configuration and number of recreation facilities and park structures throughout the study area. Most changes were additions of the smallest amenities with the smallest service area distances (e.g. playgrounds, swing sets, spraypads, tennis courts).

A spatial limitation exists in the potential for selective daily mobility biases. In essence, children with greater mobility options linked to higher household incomes have a greater opportunity to travel to health-positive environments far outside their home neighbourhood. When examining measurements involving proximity of home locations or exposures to parks and recreation spaces, this thesis may not have captured participants travelling outside of the study area to engage in such spaces. Despite that, due to concerns about climate change and carbon footprints, enticing families of higher socioeconomic status to more often use their neighbourhood amenities is a critical aspect of programming spaces that should be emphasized (Friedman, 2014). Additionally, generalizability of research findings in this thesis to other regions is preconditioned on numerous factors: city size, built environment configuration, physical geography, climate, demographic and socioeconomic makeup, and cultural milieu (Kwan, 2012a).

The strengths of this thesis research's approach and findings are numerous. Relative to similar studies, the large and socioeconomically-stratified sample size that STEAM has participant data on provided thorough representativeness and helped to reduce socioeconomic, demographic and geographic contextual biases. Rigorous GPS data collection and validation helped reduce spatial biases, and the focus on children's free time allowed linkages with their objectively-determined spatial interactions to various social and personal attributes. The thesis' comparison of measures of accessibility that link to a policy managing local parks and recreation spaces enhanced the relationships between such spaces and the children interacting with them. Additionally, integrating an extensive set of independent variables – many of which have been linked in the literature to influencing children's accessibility, exposure, and engagement to parks and recreation spaces – into a modified Socio-Ecological model strengthened scholarship regarding who, how often, and how long children of different backgrounds and lifestyles utilize parks and recreation spaces.

5.6 Avenues for Future Research

Within the research design framework of STEAM, there is potential to expand the findings from this thesis by incorporating additional data, such as combining GPS location and GIS spatial data with the activity diary and focus group data (see figure 3.1). Such combinations could expand on children's health outcomes involving exposure and engagement to types of spaces. For instance, enhancing exposure measurements by including interaction measurements to trees or water bodies can add to the overall context of a participant's activity spaces. Trees and water bodies have been associated with positive health outcomes, even if only exposed to them in short bursts (Larsen et al., 2009; Paddle & Gilliland, 2016; Pearson et al., 2017; Tillmann et al., 2018).

Incorporating tool-validated perceptual data that uncovers what children think of parks and recreation spaces (e.g. quality, accessibility, safety, social enjoyment) is salient. Among southwestern Ontario STEAM participants, barriers to engagement in spaces has been uncovered by Taylor et al. (2018); for northwest Ontario STEAM participants, it has been uncovered by

Button et al. (2020). Linking findings on barriers to exposures or engagements with different parks and recreation spaces can tease out features that entice children. Along the same lines, studies incorporating ecological momentary assessments (EMA) of participants can enhance context by incorporating qualitative data linked to when and where participants are exposed to certain types of spaces (Boettner et al., 2019; Loveday et al., 2015).

A major aspect in observational research of children and their environmental interactions is the approach of following the same participants across multiple time periods (e.g. repeated measures, time series). Longitudinal observational studies that collect spatial and socio-ecological data similar to STEAM and simultaneously update study-area environments as they change can support spatiotemporal analyses with a greater ability to predict levels of influence among variables contained in any level of the SEM. Amidst such longitudinal studies, researchers could develop and launch pilot projects that test interventions in parks and recreation spaces. Interventions involving specific park structures and recreation amenities have been attempted by researchers (Mårtensson et al., 2009; Wray et al., 2020), with varying degrees of success improving children's health outcomes or increasing exposure/engagement in such spaces. Interventions should consider how to facilitate engagement among under-engaged individual-level or interpersonal-level SEM groups of children, such as providing them with more parks and recreation amenities that match exposure findings, or by promoting increased use of the amenities. Of course, any longitudinal design or intervention should endeavor to record observation data in all seasons; doing so permits incorporation of seasonality as a moderating or mediating variable term in determining statistical relationships or formulating predictive models.

In summary, this thesis uncovered differences in methods of measuring accessibility and exposure to parks and recreation spaces among children living in Middlesex-London, Ontario. It showed how some measurement methods are inaccurately attributing distances and failing to match with objective exposures. Researchers and policymakers need to utilize more accurate measurement methods, acquire more empirically-derived data, and employ more statistically-tested distances tailored to public spaces and features. These distances are best when backed by objective exposure and engagement spatiotemporal data from a representative sample of the population the spaces and features are provisioned for – in the case of this thesis, children.

Additionally, children identified as members of certain demographic or socioeconomic groups are not provided equitable access to parks and recreation spaces as well as others, particularly those among vulnerable segments of the population. Research in this thesis highlights some of these disparities, disparities policymakers should heed in future development and programming of parks and recreation spaces. This thesis detailed data collection routines, data processing procedures, and data analysis models, all tied to children's proportions of free time in parks and recreation spaces. Many statistically significant associations and influences derived from attributes of children were uncovered with the parks and recreation spaces they were exposed to and/or engaged in. Ultimately, the thesis findings can be used to gauge how frameworks governing the provision of parks and recreation spaces are socially and spatially effective.

References

Abbade, L. P. F., Wang, M., Sriganesh, K., Mbuagbaw, L., & Thabane, L. (2016). Framing of research question using the PICOT format in randomised controlled trials of venous ulcer disease: a protocol for a systematic survey of the literature. *BMJ Open*, *6*(11), e013175. https://doi.org/10.1136/bmjopen-2016-013175

Adriaanse, J. A. (2019). The influence of gendered emotional relations on gender equality in sport governance. *Journal of Sociology (Melbourne, Vic.)*, *55*(3), 587–603. https://doi.org/10.1177/1440783319842665

Alexander, D. S., Huber, L. R. B., Piper, C. R., & Tanner, A. E. (2013). The association between recreational parks, facilities and childhood obesity: a cross-sectional study of the 2007 National Survey of Children's Health. *Journal of Epidemiology and Community Health (1979)*, *67*(5), 427–431. https://doi.org/10.1136/jech-2012-201301

Amoly, E., Dadvand, P., Forns, J., López-Vicente, M., Basagaña, X., Julvez, J., Alvarez-Pedrerol, M., Nieuwenhuijsen, M. J., & Sunyer, J. (2015). Green and blue spaces and behavioral development in barcelona schoolchildren: The BREATHE project. *Environmental Health Perspectives*, *122*(12), 1351–1358. https://doi.org/10.1289/ehp.1408215

Apparicio, P., Gelb, J., Dubé, A. S., Kingham, S., Gauvin, L., & Robitaille, É. (2017). The approaches to measuring the potential spatial access to urban health services revisited: Distance types and aggregation-error issues. *International Journal of Health Geographics*, *16*(1), 1–24. https://doi.org/10.1186/s12942-017-0105-9

Arunkumar, K., Bowman, D. D., Coen, S. E., El-Bagdady, M. A., Ergler, C. R., Gilliland, J. A., Mahmood, A., & Paul, S. (2018). Conceptualizing Youth Participation in Children's Health Research: Insights from a Youth-Driven Process for Developing a Youth Advisory Council. *Children*, *6*(1), 3. https://doi.org/10.3390/children6010003

Balseviciene, B., Sinkariova, L., Grazuleviciene, R., Andrusaityte, S., Uzdanaviciute, I., Dedele, A., & Nieuwenhuijsen, M. J. (2014). Impact of residential greenness on preschool children's emotional and behavioral problems. International Journal of Environmental Research and Public Health, 11(7), 6757–6770. https://doi.org/10.3390/ijerph110706757

Bejarano, C. M., Carlson, J. A., Cushing, C. C., Kerr, J., Saelens, B. E., Frank, L. D., Glanz, K., Cain, K. L., Conway, T. L., & Sallis, J. F. (2019). Neighbourhood built environment associations with adolescents' location-specific sedentary and screen time. *Health and Place*, *56*(January), 147–154. https://doi.org/10.1016/j.healthplace.2019.01.015

Boettner, B., Browning, C. R., & Calder, C. A. (2019). Feasibility and Validity of Geographically Explicit Ecological Momentary Assessment With Recall-Aided Space-Time Budgets. *Journal of Research on Adolescence*, *29*(3), 627–645. https://doi.org/10.1111/jora.12474

Botha, J., & Kourkoutas, E. (2016). A community of practice as an inclusive model to support children with social, emotional and behavioural difficulties in school contexts. *International Journal of Inclusive Education*, *20*(7), 784–799. https://doi.org/http://dx.doi.org/10.1080/13603116.2015.1111448

Brennan, L. K., Brownson, R. C., & Orleans, C. T. (2014). Childhood Obesity Policy Research and Practice: Evidence for Policy and Environmental Strategies. *American Journal of Preventive Medicine*, *46*(1), e1–e16. https://doi.org/http://dx.doi.org/10.1016/j.amepre.2013.08.022

Browning, M. H. E. M., & Rigolon, A. (2019). School Green Space and Its Impact on Academic Performance: A Systematic Literature Review. *International Journal of Environmental Research and Public Health*, *16*(3), 429. https://doi.org/10.3390/ijerph16030429

Brum-Bastos, V. S., Long, J. A., & Demšar, U. (2018). Weather effects on human mobility: a study using multi-channel sequence analysis. *Computers, Environment and Urban Systems*, *71*(May), 131–152. https://doi.org/10.1016/j.compenvurbsys.2018.05.004

Brussoni, M., Ishikawa, T., Brunelle, S., & Herrington, S. (2017). Landscapes for play: Effects of an intervention to promote nature-based risky play in early childhood centres. *Journal of Environmental Psychology*, *54*, 139–150. https://doi.org/10.1016/j.jenvp.2017.11.001

Brussoni, M., Lin, Y., Han, C., Janssen, I., Schuurman, N., Boyes, R., Swanlund, D., & Mâsse, L. C. (2020). A qualitative investigation of unsupervised outdoor activities for 10- to 13-year-old children: "I like adventuring but I don't like adventuring without being careful."

Journal of Environmental Psychology, *70*(June), 101460. https://doi.org/10.1016/j.jenvp.2020.101460

Burgess, A., Shah, K., Hough, O., & Hynynen, K. (2016). Association between neighbourhood walkability and GPS- measured walking, bicycling and vehicle time in adolescents. *Health & Place*, *15*(5), 477–491. https://doi.org/10.1586/14737175.2015.1028369.Focused

Bürgi, R., Tomatis, L., Murer, K., & De Bruin, E. D. (2016). Spatial physical activity patterns among primary school children living in neighbourhoods of varying socioeconomic status: A cross-sectional study using accelerometry and Global Positioning System. *BMC Public Health*, *16*(1), 1–12. https://doi.org/10.1186/s12889-016-2954-8

Buttazzoni, A. N., Coen, S. E., & Gilliland, J. A. (2018). Supporting active school travel: A qualitative analysis of implementing a regional safe routes to school program. *Social Science and Medicine*, *212*(July), 181–190. https://doi.org/10.1016/j.socscimed.2018.07.032

Button, B. (2020). Examining weather-related factors on moderate to vigorous physical activity levels of children from rural communities. *Western University Dissertation*, 1–173.

Button, B. L. G., Shah, T. I., Clark, A. F., Wilk, P., & Gilliland, J. A. (2020). Examining weather-related factors on physical activity levels of children from rural communities. *Canadian Journal of Public Health*. https://doi.org/10.17269/s41997-020-00324-3

Canada, C. F. (2020). *Top 10 threats to childhood in Canada*.

Canada, Parks (1994). *Parks Canada Guiding Principles and Operational Policies*. Parks Canada. https://books.google.ca/books?id=XAvbAAAAMAAJ

Carver, A., Veitch, J., Sahlqvist, S., Crawford, D., & Hume, C. (2014). Active transport, independent mobility and territorial range among children residing in disadvantaged areas. *Journal of Transport and Health*, *1*(4), 267–273. https://doi.org/10.1016/j.jth.2014.01.004

Chaix, B. (2018). Mobile Sensing in Environmental Health and Neighbourhood Research. *Annual Review of Public Health*, *39*(1), 367–384. https://doi.org/10.1146/annurev-publhealth-040617-013731

Chaix, B., Kestens, Y., Duncan, D. T., Brondeel, R., Méline, J., El Aarbaoui, T., Pannier, B., &

Merlo, J. (2016). A GPS-Based Methodology to Analyze Environment-Health Associations at the Trip Level: Case-Crossover Analyses of Built Environments and Walking. *American Journal of Epidemiology*, *184*(8), 579–589. https://doi.org/10.1093/aje/kww071

Chaix, B., Méline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., Lewin, A., Labadi, K., & Kestens, Y. (2013). GPS tracking in neighbourhood and health studies: A step forward for environmental exposure assessment, A step backward for causal inference? *Health and Place*, *21*, 46–51. https://doi.org/10.1016/j.healthplace.2013.01.003

Chaudhury, M., Hinckson, E., Badland, H., & Oliver, M. (2019). Children's independence and affordances experienced in the context of public open spaces: a study of diverse inner-city and suburban neighbourhoods in Auckland, New Zealand. *Children's Geographies*, *17*(1), 49–63. https://doi.org/10.1080/14733285.2017.1390546

Clark, A. F., Bent, E. A., & Gilliland, J. (2015). Shortening the trip to school: Examining how children's active school travel is influenced by shortcuts. *Environment and Planning B: Planning and Design*, *43*(3), 499–514. https://doi.org/10.1177/0265813515614678

Clark, A. F., Campbell, J., Tucker, P., Wilk, P., & Gilliland, J. A. (2019). If You Make it Free, Will They Come? Using a Physical Activity Accessibility Model to Understand the Use of a Free Children's Recreation Pass. *Journal of Physical Activity and Health*, 1–11. https://doi.org/10.1123/jpah.2018-0364

Clark, A. F., & Scott, D. M. (2016). Barriers to walking: An investigation of adults in Hamilton (Ontario, Canada). *International Journal of Environmental Research and Public Health*, *13*(2). https://doi.org/10.3390/ijerph13020179

Clark, A. F., Scott, D. M., & Yiannakoulias, N. (2014). Examining the relationship between active travel, weather, and the built environment: a multilevel approach using a GPS-enhanced dataset. *Transportation*, *41*(2), 325–338. https://doi.org/10.1007/s11116-013-9476-3

Clark, A. F., Wilk, P., Mitchell, C. A., Smith, C., Archer, J., & Gilliland, J. A. (2018). Examining How Neighbourhood Socioeconomic Status, Geographic Accessibility, and Informational Accessibility Influence the Uptake of a Free Population-Level Physical

Activity Intervention for Children. *American Journal of Health Promotion*, *32*(2), 315–324. https://doi.org/10.1177/0890117117718433

Clevenger, K. A., Sinha, G., & Howe, C. A. (2019). Comparison of Methods for Analyzing Global Positioning System and Accelerometer Data during School Recess. *Measurement in Physical Education and Exercise Science*, *23*(1), 58–68. https://doi.org/10.1080/1091367X.2018.1512495

Collins, P., Al-Nakeeb, Y., Nevill, A., & Lyons, M. (2012). The impact of the built environment on young people's physical activity patterns: Asuburban-rural comparison using GPS. *International Journal of Environmental Research and Public Health*, *9*(9), 3030–3050. https://doi.org/10.3390/ijerph9093030

Cottrell, L., Zatezalo, J., Bonasso, A., Lattin, J., Shawley, S., Murphy, E., Lilly, C., & Neal, W. A. (2015). The relationship between children's physical activity and family income in rural settings: A cross-sectional study. *Preventive Medicine Reports*, *2*, 99–104. https://doi.org/10.1016/j.pmedr.2015.01.008

Crouse, D. L., Pinault, L., Balram, A., Hystad, P., Peters, P. A., Chen, H., van Donkelaar, A., Martin, R. V., Ménard, R., Robichaud, A., & Villeneuve, P. J. (2017). Urban greenness and mortality in Canada's largest cities: a national cohort study. *The Lancet Planetary Health*, *1*(7), e289–e297. https://doi.org/10.1016/S2542-5196(17)30118-3

Cullingworth, J. B. (2017). *Urban and Regional Planning in Canada*. Taylor & Francis. https://books.google.ca/books?id=xqs0DwAAQBAJ

Drewnowski, A., Aggarwal, A., Rose, C., Gupta, S., Delaney, J. A., & Hurvitz, P. M. (2019). Activity space metrics not associated with sociodemographic variables, diet or health outcomes in the Seattle Obesity Study II. *Spatial and Spatio-Temporal Epidemiology*, *30*, 100289. https://doi.org/10.1016/j.sste.2019.100289

DuBreck, C. M., Sadler, R. C., Arku, G., & Gilliland, J. A. (2018). Examining community and consumer food environments for children: An urban-suburban-rural comparison in Southwestern Ontario. *Social Science and Medicine*, *209*(April), 33–42. https://doi.org/10.1016/j.socscimed.2018.05.004

Dunton, G. F., Almanza, E., Jerrett, M., Wolch, J., & Pentz, M. A. (2014). Neighbourhood park use by children: Use of accelerometry and global positioning systems. *American Journal of Preventive Medicine*, *46*(2), 136–142. https://doi.org/10.1016/j.amepre.2013.10.009

Erickson, K., & Côté, J. (2016). An Exploratory Examination of Interpersonal Interactions between Peers in Informal Sport Play Contexts. *PloS One*, *11*(5), e0154275. https://doi.org/10.1371/journal.pone.0154275

Eriksson, M., Ghazinour, M., & Hammarström, A. (2018). Different uses of Bronfenbrenner's ecological theory in public mental health research: what is their value for guiding public mental health policy and practice? *Social Theory and Health*, *16*(4), 414–433. https://doi.org/10.1057/s41285-018-0065-6

Felver, J. C., Jones, R., Killam, M. A., Kryger, C., Race, K., & Mcintyre, L. L. (2017). Contemplative Intervention Reduces Physical Interventions for Children in Residential Psychiatric Treatment. *Prevention Science*, *18*(2), 164–173. https://doi.org/http://dx.doi.org/10.1007/s11121-016-0720-x

Fitch, D. T., Rhemtulla, M., & Handy, S. L. (2018). The relation of the road environment and bicycling attitudes to usual travel mode to school in teenagers. *Transportation Research Part A: Policy and Practice*, *xxxx*, 0–1. https://doi.org/10.1016/j.tra.2018.06.013

Friedman, A. (2014). *Fundamentals of Sustainable Neighbourhoods* (2015th ed.). Springer International Publishing AG. https://doi.org/10.1007/978-3-319-10747-9

Fritz, C. E., Schuurman, N., Robertson, C., & Lear, S. (2013). A scoping review of spatial cluster analysis techniques for point-event data. *Geospatial Health*, *7*(2), 183–198. https://doi.org/10.4081/gh.2013.79

Garrett, J. K., White, M. P., Elliott, L. R., Wheeler, B. W., & Fleming, L. E. (2020). Urban nature and physical activity: Investigating associations using self-reported and accelerometer data and the role of household income. *Environmental Research*, 109899.

Gilliland, Jason A, Rangel, C. Y., Healy, M. A., Tucker, P., Loebach, J. E., Hess, P. M., He, M., Irwin, J. D., & Wilk, P. (2012). Linking Childhood Obesity to the Built Environment: A Multi-level Analysis of Home and School Neighbourhood Factors Associated With Body

Mass Index. *Canadian Journal of Public Health*, *103*(9), 15–21. https://doi.org/10.17269/CJPH.103.3283

Gilliland, Jason Andrew, Sadler, R., Clark, A. F., O'Connor, C., Milczarek, M., & Doherty, S. T. (2015). Using a smartphone application to promote healthy dietary behaviours and local food consumption. *BioMed Research International*, *2015*, 1–11. https://doi.org/10.1155/2015/841368

Gong, L., Morikawa, T., Yamamoto, T., & Sato, H. (2014). Deriving Personal Trip Data from GPS Data: A Literature Review on the Existing Methodologies. *Procedia - Social and Behavioral Sciences*, *138*(0), 557–565. https://doi.org/10.1016/j.sbspro.2014.07.239

Greer, A. E., Marcello, R., & Graveline, R. (2015). Community Members' Assessment of the Physical Activity Environments in Their Neighbourhood Parks: Utility of the Community Stakeholder Park Audit Tool. *Health Promotion Practice*, *16*(2), 202–209. https://doi.org/10.1177/1524839914551366

Grewal, T. S. K. (2013). *Awareness of physical activity levels and sedentary behaviour [electronic resource] : an assessment of awareness of physical activity levels and sedentary behaviour among parents and children / by Tripat Simran Kaur Grewal.* School of Graduate and Postdoctoral Studies, University of Western Ontario.

Healy, M. (2018). Quantifying the magnitude of environmental exposure misclassification when using imprecise address proxies in public health research. *UwO PhD Dissertations*, *1*.

Healy, M. A., & Gilliland, J. A. (2012). Quantifying the magnitude of environmental exposure misclassification when using imprecise address proxies in public health research. *Spatial and Spatio-Temporal Epidemiology*, *3*(1), 55–67. https://doi.org/10.1016/j.sste.2012.02.006

Herrador-Colmenero, M., Harrison, F., Villa-González, E., Rodríguez-López, C., Ortega, F. B., R, J., Jones, A. P., & Chillón, P. (2018). Longitudinal associations between weather, season, and mode of commuting to school amongst Spanish youths. *Scandinavian Journal of Medicine & Science in Sports*, 0–3. https://doi.org/10.1111/sms.13268

Horton, J., & Kraftl, P. (2018). Three playgrounds: Researching the multiple geographies of children's outdoor play. Environment and Planning A, 50(1), 214–235.

https://doi.org/10.1177/0308518X17735324

Ikeda, E., Stewart, T., Garrett, N., Egli, V., Mandic, S., Hosking, J., Witten, K., Hawley, G., Tautolo, E. S., Rodda, J., Moore, A., & Smith, M. (2018). Built environment associates of active school travel in New Zealand children and youth: A systematic meta-analysis using individual participant data. *Journal of Transport & Health*, *9*, 117–131. https://doi.org/10.1016/j.jth.2018.04.007

Jenks, G. F. (1967). The Data Model Concept in Statistical Mapping. *International Yearbook of Cartography*, *7*, 186–190.

Jones, A. P., Coombes, E. G., Griffin, S. J., & van Sluijs, E. M. F. (2009). Environmental supportiveness for physical activity in English schoolchildren: A study using Global Positioning Systems. *International Journal of Behavioral Nutrition and Physical Activity*, *6*, 1–8. https://doi.org/10.1186/1479-5868-6-42

Kalkhan, M. A. (2011). *Spatial statistics : geospatial information modeling and thematic mapping / by Mohammed A. Kalkhan.* (First edit). CRC Press, an imprint of Taylor and Francis. https://doi.org/10.1201/9781439891117

Kang, Y., Cho, N., & Son, S. (2018). Spatiotemporal characteristics of elderly population's traffic accidents in Seoul using space-time cube and space-time kernel density estimation. *PloS One*, *13*(5), e0196845. https://doi.org/10.1371/journal.pone.0196845

Katapally, T., Rainham, D., & Muhajarine, N. (2016). The Influence of Weather Variation, Urban Design and Built Environment on Objectively Measured Sedentary Behaviour in Children. *AIMS Public Health*, *3*(4), 663–681. https://doi.org/10.3934/publichealth.2016.4.663

Kerr, J., Duncan, S., & Schipperjin, J. (2011). Using global positioning systems in health research: A practical approach to data collection and processing. *American Journal of Preventive Medicine*, *41*(5), 532–540. https://doi.org/10.1016/j.amepre.2011.07.017

Kestens, Y., Thierry, B., & Chaix, B. (2016a). Re-creating daily mobility histories for health research from raw GPS tracks: Validation of a kernel-based algorithm using real-life data. *Health and Place*, *40*, 29–33. https://doi.org/10.1016/j.healthplace.2016.04.004

Kestens, Y., Thierry, B., & Chaix, B. (2016b). Re-creating daily mobility histories for health research from raw GPS tracks: Validation of a kernel-based algorithm using real-life data. *Health & Place*, *40*, 29–33. https://doi.org/10.1016/j.healthplace.2016.04.004

Kestens, Y., Thierry, B., Shareck, M., Steinmetz-Wood, M., & Chaix, B. (2018). Integrating activity spaces in health research: Comparing the VERITAS activity space questionnaire with 7-day GPS tracking and prompted recall. *Spatial and Spatio-Temporal Epidemiology*, *25*, 1–9. https://doi.org/10.1016/j.sste.2017.12.003

Khalilzadeh, J., & Tasci, A. D. A. (2017). Large sample size, significance level, and the effect size: Solutions to perils of using big data for academic research. *Tourism Management*, *62*, 89–96.

Kossuth, R. S. (2005). Spaces and Places to Play: The Formation of a Municipal Parks System in London, Ontario, 1867-1914. *Ontario History*, *97*(2), 160–190. https://doi.org/10.7202/1065881ar

Krenn PJ, Titze S, Oja P, Jones A, Ogilvie D. Use of global positioning systems to study physical activity and the environment: a systematic review. Am J Prev Med. 2011 Nov;41(5):508-15. doi: 10.1016/j.amepre.2011.06.046. PMID: 22011423; PMCID: PMC3821057.

Kwan, M. P. (2012a). How GIS can help address the uncertain geographic context problem in social science research. *Annals of GIS*, *18*(4), 245–255. https://doi.org/10.1080/19475683.2012.727867

Kwan, M. P. (2012b). The Uncertain Geographic Context Problem. *Annals of the Association of American Geographers*, *102*(5), 958–968. https://doi.org/10.1080/00045608.2012.687349

Kwan, M. P., Wang, D., Richardson, D., & Zhou, C. (2015). Space-time integration in geography and GIScience: Research frontiers in the US and China. In *Space-Time Integration in Geography and GIScience: Research Frontiers in the US and China*. https://doi.org/10.1007/978-94-017-9205-9

Kwan, M. P., Wang, J., Tyburski, M., Epstein, D. H., Kowalczyk, W. J., & Preston, K. L. (2018). Uncertainties in the geographic context of health behaviors: a study of substance users' exposure to psychosocial stress using GPS data. *International Journal of Geographical Information Science*, *00*(00), 1–20. https://doi.org/10.1080/13658816.2018.1503276

Kweon, B. S., Ellis, C. D., Lee, J., & Jacobs, K. (2017). The link between school environments and student academic performance. *Urban Forestry and Urban Greening*, *23*, 35–43. https://doi.org/10.1016/j.ufug.2017.02.002

Larsen, K., Gilliland, J., Hess, P., Tucker, P., Irwin, J., & He, M. (2009). The influence of the physical environment and sociodemographic characteristics on children's mode of travel to and from school. *American Journal of Public Health*, *99*(3), 520–526. https://doi.org/10.2105/AJPH.2008.135319

Lewis, L. K., Maher, C., Belanger, K., Tremblay, M., Chaput, J. P., & Olds, T. (2016). At the Mercy of the Gods: Associations between weather, physical activity, and sedentary time in children. *Pediatric Exercise Science*, *28*(1), 152–163. https://doi.org/10.1123/pes.2015-0076

Li, D., & Sullivan, W. C. (2016). Impact of views to school landscapes on recovery from stress and mental fatigue. *Landscape and Urban Planning*, *148*, 149–158. https://doi.org/10.1016/j.landurbplan.2015.12.015

Loebach, J. E., & Gilliland, J. A. (2016). Free Range Kids? Using GPS-Derived Activity Spaces to Examine Children's Neighbourhood Activity and Mobility. *Environment and Behavior*, *48*(3), 421–453. https://doi.org/10.1177/0013916514543177

Loebach, J., & Gilliland, J. (2016). Neighbourhood play on the endangered list: examining patterns in children's local activity and mobility using GPS monitoring and qualitative GIS. *Children's Geographies*, *14*(5), 573–589. https://doi.org/10.1080/14733285.2016.1140126

Loebach, J., & Gilliland, J. (2019). Examining the Social and Built Environment Factors Influencing Children's Independent Use of Their Neighbourhoods and the Experience of Local Settings as Child-Friendly. *Journal of Planning Education and Research*, *December 2018*, 0739456X1982844. https://doi.org/10.1177/0739456X19828444

Loveday, A., Sherar, L. B., Sanders, J. P., Sanderson, P. W., & Esliger, D. W. (2015). Technologies that assess the location of physical activity and sedentary behavior: A systematic review. *Journal of Medical Internet Research*, *17*(8). https://doi.org/10.2196/jmir.4761

Määttä, S., Ray, C., Vepsäläinen, H., Lehto, E., Kaukonen, R., Ylönen, A., & Roos, E. (2018). Parental education and pre-School children's objectively measured sedentary time: The role of co-participation in physical activity. *International Journal of Environmental Research and Public Health*, *15*(2), 1–14. https://doi.org/10.3390/ijerph15020366

Maddison, R., Jiang, Y., Vander Hoorn, S., Exeter, D., Mhurchu, C. N., & Dorey, E. (2010). Describing patterns of physical activity in adolescents using global positioning systems and acceleromet. *Pediatric Exercise Science*, *22*(3), 392–407. https://doi.org/10.1123/pes.22.3.392

Madley-Dowd, P., Hughes, R., Tilling, K., & Heron, J. (2019). The proportion of missing data should not be used to guide decisions on multiple imputation. Journal of Clinical Epidemiology, 110, 63–73. https://doi.org/10.1016/j.jclinepi.2019.02.016

Marquet, O., Aaron Hipp, J., Alberico, C., Huang, J. H., Fry, D., Mazak, E., Lovasi, G. S., & Floyd, M. F. (2019). Park use preferences and physical activity among ethnic minority children in low-income neighbourhoods in New York City. *Urban Forestry and Urban Greening*, *38*(September 2018), 346–353. https://doi.org/10.1016/j.ufug.2019.01.018

Marquet, O., Hipp, J. A., Alberico, C., Huang, J.-H., Fry, D., Mazak, E., Lovasi, G. S., & Floyd, M. F. (2019). Park use preferences and physical activity among ethnic minority children in low-income neighbourhoods in New York City. *Urban Forestry & Urban Greening*, *38*, 346–353.

Mårtensson, F., Boldemann, C., Söderström, M., Blennow, M., Englund, J. E., & Grahn, P. (2009). Outdoor environmental assessment of attention promoting settings for preschool children. *Health and Place*, *15*(4), 1149–1157. https://doi.org/10.1016/j.healthplace.2009.07.002

Matz, C. J., Stieb, D. M., Davis, K., Egyed, M., Rose, A., Chou, B., & Brion, O. (2014). Effects of age, season, gender and urban-rural status on time-activity: Canadian human activity pattern survey 2 (CHAPS 2). *International Journal of Environmental Research and Public*

Health, *11*(2), 2108–2124. https://doi.org/10.3390/ijerph110202108

McCormack, L. A., & Meendering, J. (2016). Diet and Physical Activity in Rural vs Urban Children and Adolescents in the United States: A Narrative Review. *Journal of the Academy of Nutrition and Dietetics*, *116*(3), 467–480. https://doi.org/10.1016/j.jand.2015.10.024

McCree, M., Cutting, R., & Sherwin, D. (2018). The Hare and the Tortoise go to Forest School: taking the scenic route to academic attainment via emotional wellbeing outdoors. *Early Child Development and Care*, *188*(7), 980–996. https://doi.org/10.1080/03004430.2018.1446430

McCrorie, P. R. W., Fenton, C., & Ellaway, A. (2014). Combining GPS, GIS and accelerometry to explore the physical activity and evironment relationship in children and young people - a review. *International Journal of Behavioral Nutrition and Physical Activity*, *11*(93).

McCullough, A. K., Keller, B. S., Qiu, S., & Garber, C. E. (2018). Analysis of accelerometer-derived interpersonal spatial proximities: A calibration, simulation, and validation study. *Measurement in Physical Education and Exercise Science*, *22*(3), 275–286. https://doi.org/10.1080/1091367X.2018.1437039

McGrath, L. J., Hopkins, W. G., & Hinckson, E. A. (2015). Associations of Objectively Measured Built-Environment Attributes with Youth Moderate–Vigorous Physical Activity: A Systematic Review and Meta-Analysis. *Sports Medicine*, *45*(6), 841–865. https://doi.org/10.1007/s40279-015-0301-3

Mehtälä, M. A. K., Sääkslahti, A. K., Inkinen, M. E., & Poskiparta, M. E. H. (2014). A socio-ecological approach to physical activity interventions in childcare: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *11*(1). https://doi.org/10.1186/1479-5868-11-22

Meyer, M. R. U., Moore, J. B., Abildso, C., Edwards, M. B., Gamble, A., & Baskin, M. L. (2016). Rural active living: A call to action. *Journal of Public Health Management and Practice*, *22*(5), E11–E20. https://doi.org/10.1097/PHH.0000000000000333

Mitchell, C. (2016). *Children's Physical Activity and the Built Environment: The Impact of*

Neighbourhood Opportunities and Contextual Environmental Exposure. *UwO Thesis*(March). https://doi.org/10.3390/ijerph13010130

Mitchell, C. A., Clark, A. F., & Gilliland, J. A. (2016). Built environment influences of children's physical activity: Examining differences by neighbourhood size and sex. *International Journal of Environmental Research and Public Health*, *13*(1). https://doi.org/10.3390/ijerph13010130

Molnar, B. E., Gortmaker, S. L., Bull, F. C., & Buka, S. L. (2004). Unsafe to Play? Neighbourhood Disorder and Lack of Safety Predict Reduced Physical Activity among Urban Children and Adolescents. *American Journal of Health Promotion*, *18*(5), 378–386. https://doi.org/10.4278/0890-1171-18.5.378

Moore, R. C. (1986). *Childhood's domain: play and place in child development Croom Helm*. London.

Mudge, J., Baker, L., Edge, C., & Houlahan, J. (2012). Setting an Optimal α That Minimizes Errors in Null Hypothesis Significance Tests. *PLoS ONE*, *7*, e32734. https://doi.org/10.1371/journal.pone.0032734

Nykiforuk, C. I. J., Atkey, K., Brown, S., Caldwell, W., Galloway, T., Gilliland, J., Kongats, K., McGavock, J., & Raine, K. D. (2018). Promotion of physical activity in rural, remote and northern settings: a Canadian call to action. Health Promotion and Chronic Disease Prevention in Canada: Research, Policy and Practice, 38(11), 419–435. https://doi.org/10.24095/hpcdp.38.11.03

O'Brien, L. (2009). Learning outdoors: the Forest School approach. *Education 3-13*, *37*(1), 45–60. https://doi.org/10.1080/03004270802291798

Pacchi, C. (2018). Epistemological critiques to the technocratic planning model: the role of Jane Jacobs, Paul Davidoff, Reyner Banham and Giancarlo De Carlo in the 1960s. *City, Territory and Architecture*, *5*(1), 1–8. https://doi.org/10.1186/s40410-018-0095-3

Paddle, E., & Gilliland, J. (2016). Orange is the new green: Exploring the restorative capacity of seasonal foliage in schoolyard trees. *International Journal of Environmental Research and Public Health*, *13*(5). https://doi.org/10.3390/ijerph13050497

ParticipACTION. (2020). *2020 Report Card #Family influence.* https://doi.org/10.7748/nop2013.12.25.10.41.s21

Patrick, K. (2009). A Tool for Geospatial Analysis of Physical Activity: Physical Activity Location Measurement System (PALMS). *Medicine and Science in Sports and Exercise*, *41*, 10. https://doi.org/10.1249/01.MSS.0000352671.76607.56

Pearson, A. L., Bottomley, R., Chambers, T., Thornton, L., Stanley, J., Smith, M., Barr, M., & Signal, L. (2017). Measuring Blue Space Visibility and “Blue Recreation” in the Everyday Lives of Children in a Capital City. *International Journal of Environmental Research and Public Health*, *14*(6), 563. https://doi.org/10.3390/ijerph14060563

Pratt, M., Macera, C. A., Sallis, J. F., O’Donnell, M., & Frank, L. D. (2004). Economic interventions to promote physical activity: application of the SLOTH model. *American Journal of Preventive Medicine*, *27*(3), 136–145.

Prince, S. A., Butler, G. P., Rao, D. P., & Thompson, W. (2019). Where are children and adults physically active and sedentary? – A rapid review of location-based studies. *Health Promotion and Chronic Disease Prevention in Canada*, *39*(3), 67–103. https://doi.org/10.24095/hpcdp.39.3.01

Prince, S. A., Melvin, A., Roberts, K. C., Butler, G. P., & Thompson, W. (2020). Sedentary behaviour surveillance in Canada: Trends, challenges and lessons learned. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(1). https://doi.org/10.1186/s12966-020-00925-8

Putnam, R. D. (2000). *Bowling Alone: The Collapse and Revival of American Community*. Simon & Schuster. http://bowlingalone.com/

Remmers, T., Thijs, C., Ettema, D., de Vries, S., Slingerland, M., & Kremers, S. (2019). Critical hours and important environments: Relationships between afterschool physical activity and the physical environment using GPS, GIS and accelerometers in 10–12-year-old children. *International Journal of Environmental Research and Public Health*, *16*(17). https://doi.org/10.3390/ijerph16173116

Richard, L. (2014). *Exploring the association between commute to school duration and* *chlidren's physical activity level and bodyweight status* (Issue August).

Robson, V. (2012). Land fragmentation in southern Ontario: A tragedy of the spatial anticommons. *SURG Journal*, *5*(2), 22–27.

Sadler, R. C., & Gilliland, J. A. (2015). Comparing children's GPS tracks with geospatial proxies for exposure to junk food. *Spatial and Spatio-Temporal Epidemiology*, *14–15*, 55–61. https://doi.org/10.1016/j.sste.2015.09.001

Sadler, R. C., Gilliland, J. A., & Arku, G. (2011). An application of the edge effect in measuring accessibility to multiple food retailer types in Southwestern Ontario, Canada. *International Journal of Health Geographics*, *10*(1), 34. https://doi.org/10.1186/1476-072X-10-34

Sandercock, G., Angus, C., & Barton, J. (2010). Physical activity levels of children living in different built environments. *Preventive Medicine*, *50*(4), 193–198. https://doi.org/10.1016/j.ypmed.2010.01.005

Schieman, K. (2018). Relationship between the physical environment with children's health behaviours and outcomes. *UwO Masters Thesis*.

Schoeppe, S., Duncan, M. J., Badland, H. M., Rebar, A. L., & Vandelanotte, C. (2016). Too far from home? Adult attitudes on children's independent mobility range. *Children's Geographies*, *14*(4), 482–489. https://doi.org/10.1080/14733285.2015.1116685

Shen, L., & Stopher, P. R. (2014). Review of GPS Travel Survey and GPS Data-Processing Methods. *Transport Reviews*, *34*(3), 316–334. https://doi.org/10.1080/01441647.2014.903530

Shmool, J. L. C., Johnson, I. L., Dodson, Z. M., Keene, R., Gradeck, R., Beach, S. R., & Clougherty, J. E. (2018). Developing a GIS-Based Online Survey Instrument to Elicit Perceived Neighbourhood Geographies to Address the Uncertain Geographic Context Problem. *Professional Geographer*, *70*(3), 423–433. https://doi.org/10.1080/00330124.2017.1416299

Siu, K. W. M. (2013). Accessible park environments and facilities for the visually impaired. *Facilities*, *31*(13/14), 590–609. https://doi.org/10.1108/f-10-2011-0079

Smith, A. L., Troped, P. J., McDonough, M. H., & DeFreese, J. D. (2015). Youth perceptions of how neighbourhood physical environment and peers affect physical activity: A focus group study. *International Journal of Behavioral Nutrition and Physical Activity*, *12*(1), 1–9. https://doi.org/10.1186/s12966-015-0246-9

Smith, E. P., & Bradshaw, C. P. (2017). Promoting Nurturing Environments in Afterschool Settings. *Clinical Child and Family Psychology Review*, *20*(2), 117–126. https://doi.org/10.1007/s10567-017-0239-0

Smith, L., Foley, L., & Panter, J. (2019). Activity spaces in studies of the environment and physical activity: a review and synthesis of implications for causality. *Health & Place*, *March*, 102113. https://doi.org/10.1016/j.healthplace.2019.04.003

Tallis, H., Bratman, G. N., Samhouri, J. F., & Fargione, J. (2018). Are California elementary school test scores more strongly associated with urban trees than poverty? *Frontiers in Psychology*, *9*(OCT), 1–8. https://doi.org/10.3389/fpsyg.2018.02074

Taylor, L., Clark, A., Wilk, P., Button, B., & Gilliland, J. (2018). Exploring the Effect of Perceptions on Children's Physical Activity in Varying Geographic Contexts: Using a Structural Equation Modelling Approach to Examine a Cross-Sectional Dataset. *Children*, *5*(12), 159. https://doi.org/10.3390/children5120159

Tester, J., & Baker, R. (2009). Making the playfields even: Evaluating the impact of an environmental intervention on park use and physical activity. *Preventive Medicine*, *48*(4), 316–320. https://doi.org/10.1016/j.ypmed.2009.01.010

Thierry, B., Chaix, B., & Kestens, Y. (2013). Detecting activity locations from raw GPS data: A novel kernel-based algorithm. *International Journal of Health Geographics*, *12*, 1–10. https://doi.org/10.1186/1476-072X-12-14

Thompson, S., Kent, J., & Lyons, C. (2014). Building partnerships for healthy environments: research, leadership and education. *Health Promotion Journal of Australia*, *24*(3), 202–208. https://doi.org/http://dx.doi.org/10.1071/HE14039

Tillmann, S., Clark, A. F., & Gilliland, J. A. (2018). Children and nature: Linking accessibility of natural environments and children's health-related quality of life. *International Journal of*

Environmental Research and Public Health, *15*(6). https://doi.org/10.3390/ijerph15061072

Tillmann, S., Tobin, D., Avison, W., & Gilliland, J. (2018). Mental health benefits of interactions with nature in children and teenagers: a systematic review. *Journal of Epidemiology and Community Health*, *0*, 1–9. https://doi.org/10.1136/jech-2018-210436

Timperio, A., Giles-Corti, B., Crawford, D., Andrianopoulos, N., Ball, K., Salmon, J., & Hume, C. (2008). Features of public open spaces and physical activity among children: Findings from the CLAN study. *Preventive Medicine*, *47*(5), 514–518. https://doi.org/10.1016/j.ypmed.2008.07.015

Timperio, A., Reid, J., & Veitch, J. (2015). Playability: Built and Social Environment Features That Promote Physical Activity Within Children. *Current Obesity Reports*, *4*(4), 460–476. https://doi.org/10.1007/s13679-015-0178-3

Toftager, M., Christiansen, L. B., Ersbøll, A. K., Kristensen, P. L., Due, P., & Troelsen, J. (2014). Intervention effects on adolescent physical activity in the multicomponent SPACE study: A cluster randomized controlled trial. *PLoS ONE*, *9*(6), 1–12. https://doi.org/10.1371/journal.pone.0099369

Toumbourou, J. W., Hemphill, S. A., Tresidder, J., Humphreys, C., Edwards, J., & Murray, D. (2007). Mental health promotion and socio-economic disadvantage: lessons from substance abuse, violence and crime prevention and child health. *Health Promotion Journal of Australia*, *18*(3), 184–190. https://www.lib.uwo.ca/cgi-bin/ezpauthn.cgi?url=http://search.proquest.com/docview/207441751?accountid=15115

Townsend, N., & Foster, C. (2013). Developing and applying a socio-ecological model to the promotion of healthy eating in the school. *Public Health Nutrition*, *16*(6), 1101–1108. https://doi.org/10.1017/S1368980011002655

Tucker, P, & Gilliland, J. (2007). The effect of season and weather on physical activity: A systematic review. *Public Health*, *121*(12), 909–922. https://doi.org/10.1016/j.puhe.2007.04.009

Tucker, Patricia, Irwin, J. D., Gilliland, J., He, M., Larsen, K., & Hess, P. (2009). Environmental influences on physical activity levels in youth. *Health and Place*, *15*(1), 357–363.

https://doi.org/10.1016/j.healthplace.2008.07.001

Van Hecke, L., Deforche, B., Van Dyck, D., De Bourdeaudhuij, I., Veitch, J., & Van Cauwenberg, J. (2016). Social and physical environmental factors influencing adolescents' physical activity in urban public open spaces: A qualitative study using walk-along interviews. *PLoS ONE*, *11*(5), 1–25. https://doi.org/10.1371/journal.pone.0155686

Van Hecke, L., Ghekiere, A., Veitch, J., Van Dyck, D., Van Cauwenberg, J., Clarys, P., & Deforche, B. (2018). Public open space characteristics influencing adolescents' use and physical activity: A systematic literature review of qualitative and quantitative studies. *Health and Place*, *51*(July 2017), 158–173. https://doi.org/10.1016/j.healthplace.2018.03.008

Varni, J. W., Burwinkle, T. M., & Seid, M. (2005). The PedsQL™ as a pediatric patient-reported outcome: reliability and validity of the PedsQL™ Measurement Model in 25,000 children. *Expert Review of Pharmacoeconomics & Outcomes Research*, *5*(6), 705–719. https://doi.org/10.1586/14737167.5.6.705

Veitch, J., Ball, K., Crawford, D., Abbott, G. R., & Salmon, J. (2012). Park improvements and park activity: A natural experiment. *American Journal of Preventive Medicine*, *42*(6), 616–619. https://doi.org/10.1016/j.amepre.2012.02.015

Veitch, J., Salmon, J., Parker, K., Bangay, S., Deforche, B., & Timperio, A. (2016). Adolescents' ratings of features of parks that encourage park visitation and physical activity. *International Journal of Behavioral Nutrition and Physical Activity*, *13*(1), 1–10. https://doi.org/10.1186/s12966-016-0391-9

Villa-González, E., Barranco-Ruiz, Y., Evenson, K. R., & Chillón, P. (2018). Systematic review of interventions for promoting active school transport. *Preventive Medicine*, *111*, 115–134. https://doi.org/10.1016/j.ypmed.2018.02.010

Wang, Jing, He, X., & Xu, X. (2018). The measurement of time spent outdoors in child myopia research: a systematic review. *International Journal of Ophthalmology*, *11*(6), 1045–1052. https://doi.org/10.18240/ijo.2018.06.24

Wang, Jue, & Kwan, M. P. (2018). An analytical framework for integrating the spatiotemporal dynamics of environmental context and individual mobility in exposure assessment: A study on the relationship between food environment exposures and body weight. *International Journal of Environmental Research and Public Health*, *15*(9). https://doi.org/10.3390/ijerph15092022

Wang, Jue, Kwan, M. P., & Chai, Y. (2018). An innovative context-based crystal-growth activity space method for environmental exposure assessment: A study using GIS and GPS trajectory data collected in Chicago. *International Journal of Environmental Research and Public Health*, *15*(4), 1–24. https://doi.org/10.3390/ijerph15040703

Ward, J. S., Duncan, J. S., Jarden, A., & Stewart, T. (2016). The impact of children's exposure to greenspace on physical activity, cognitive development, emotional wellbeing, and ability to appraise risk. *Health and Place*, *40*, 44–50. https://doi.org/10.1016/j.healthplace.2016.04.015

Webber, L. S., Catellier, D. J., Lytle, L. A., Murray, D. M., Pratt, C. A., Young, D. R., Elder, J. P., Lohman, T. G., Stevens, J., Jobe, J. B., & Pate, R. R. (2008). Promoting Physical Activity in Middle School Girls. Trial of Activity for Adolescent Girls. *American Journal of Preventive Medicine*, *34*(3), 173–184. https://doi.org/10.1016/j.amepre.2007.11.018

Wells, N. M., Myers, B. M., & Henderson, C. R. (2014). School gardens and physical activity: A randomized controlled trial of low-income elementary schools. *Preventive Medicine*, *69*(S), S27–S33. https://doi.org/10.1016/j.ypmed.2014.10.012

Wilk, P., Clark, A. F., Maltby, A., Smith, C., Tucker, P., & Gilliland, J. A. (2018). Examining individual, interpersonal, and environmental influences on children's physical activity levels. *SSM - Population Health*, *4*(June 2017), 76–85. https://doi.org/10.1016/j.ssmph.2017.11.004

Wilk, P., Clark, A. F., Maltby, A., Tucker, P., & Gilliland, J. A. (2018). Exploring the effect of parental influence on children's physical activity: The mediating role of children's perceptions of parental support. *Preventive Medicine*, *106*(October 2017), 79–85. https://doi.org/10.1016/j.ypmed.2017.10.018

Williams, G. C., Borghese, M. M., & Janssen, I. (2018). Neighbourhood walkability and objectively measured active transportation among 10–13 year olds. *Journal of Transport and Health*, *8*(December), 202–209. https://doi.org/10.1016/j.jth.2017.12.006

Wilson, K., Clark, A. F., & Gilliland, J. (2018). Understanding child and parent perceptions of barriers influencing children's active school travel. *BMC Public Health*, 1–14. https://doi.org/10.1186/s12889-018-5874-y12889_2018_5874

Wood, L., Giles-Corti, B., Zubrick, S. R., & Bulsara, M. K. (2013). "Through the Kids... We Connected With Our Community": Children as Catalysts of Social Capital. *Environment and Behavior*, *45*(3), 344–368. https://doi.org/10.1177/0013916511429329

Woodland, M. H. (2008). Whatcha Doin' After School? *Urban Education*, *43*(5), 537–560. https://doi.org/http://dx.doi.org/10.1177/0042085907311808

Wray, A., Martin, G., Ostermeier, E., Medeiros, A., Little, M., Reilly, K., & Gilliland, J. (2020). Physical activity and social connectedness interventions in outdoor spaces among children and youth: A rapid review. *Health Promotion and Chronic Disease Prevention in Canada*, *40*(4), 104–115. https://doi.org/10.24095/hpcdp.40.4.02

Wu, C. Da, McNeely, E., Cedeño-Laurent, J. G., Pan, W. C., Adamkiewicz, G., Dominici, F., Lung, S. C. C., Su, H. J., & Spengler, J. D. (2014). Linking student performance in Massachusetts elementary schools with the "greenness" of school surroundings using remote sensing. *PLoS ONE*, *9*(10), 1–9. https://doi.org/10.1371/journal.pone.0108548

Wu, S., Cohen, D., Shi, Y., Pearson, M., & Sturm, R. (2011). Economic Analysis of Physical Activity Interventions. *American Journal of Preventive Medicine*, *40*(2), 149–158. https://doi.org/10.1016/j.amepre.2010.10.029

Yip, C., Sarma, S., & Wilk, P. (2016). The association between social cohesion and physical activity in canada: A multilevel analysis. *SSM - Population Health*, *2*(June), 718–723. https://doi.org/10.1016/j.ssmph.2016.09.010

Yue, Y., Lan, T., Yeh, A. G. O., & Li, Q.-Q. (2014). Zooming into individuals to understand the collective: A review of trajectory-based travel behaviour studies. *Travel Behaviour and Society*, *1*(2), 69–78. https://doi.org/10.1016/j.tbs.2013.12.002

Appendices

Appendix A: List of Hand-Searched Journals

1. American Journal of Health Promotion
2. American Journal of Public Health
3. BMC Public Health
4. Canadian Journal of Public Health
5. Children, Youth and Environments
6. Children's Geographies
7. Computers, Environment and Urban Systems
8. Environment and Behavior
9. Health and Place
10. International Journal of Behavioral Nutrition and Physical Activity
11. International Journal of Environmental Research and Public Health
12. International Journal of Health Geographics
13. Journal of Medical Internet Research
14. Journal of Transport & Health
15. Spatial and Spatio-temporal Epidemiology
16. Transport Reviews
17. Transportation Research Parts A/B/C/D/E/F
18. Travel Behaviour and Society

Appendix B: Effective Public Health Practice Project (EPHPP) Quality Assessment Tool, with Added GPS Questions

EPHPP tool can be viewed here: https://merst.ca/wp-content/uploads/2018/02/quality-assessment-tool_2010.pdf

1. Is justification for the recording interval/epoch of GPS logger provided?

   a. Yes
   b. Partially
   c. No

2. If research design paired them up, was the synchronization process for recording devices (i.e. GPSr, accelerometers, heart-rate monitors) discussed and justified?

   a. Yes
   b. Partially
   c. No

3. Was post-processing of GPS data to account for errors conducted and discussed?

   a. Yes
   b. Partially
   c. No

4. Rate the quality of the study's discussion of accuracy/precision issues inherent with GPS technology (e.g. examination of geometric precision values, # of satellites, canyonization, cold starts)

   a. Thorough
   b. Partial
   c. Nonexistent

5. Does the study factor in weather or seasonality, either by admitting bias/limitation in collecting data in one season or good-weather-days, or by ensuring collection in a variety of seasons and daily weather conditions?

   a. Multiple seasons and/or weather conditions reported and controlled for
   b. Season and/or daily weather conditions reported and discussed as a limitation
   c. Season and/or daily weather conditions not reported or not discussed as a limitation

Appendix C: STEAM survey variables recorded or missing from valid participants

Survey Variable	Recorded	Missing	Total	% Missing	Imputation Approach
Age	850	6	856	0.71%	Mean*
Gender	854	2	856	0.23%	Mode*
Visible Minority Status	816	40	856	4.90%	Multiple Imputation
Household Income	467	389	856	45.44%	Missing Category
Number of Siblings	817	39	856	4.77%	Multiple Imputation
Father's Education Level	634	222	856	35.02%	Multiple Imputation
Mother's Education Level	659	197	856	29.89%	Multiple Imputation
Dog Ownership	708	148	856	20.90%	Multiple Imputation
Number Vehicles in Home	675	181	856	26.81%	Multiple Imputation
Urbanicity	845	11	856	1.30%	Mode*
Parent PA^ Encouragement Level	599	257	856	42.90%	Multiple Imputation
Asthma Status	803	53	856	6.20%	Multiple Imputation
Lone Parent Household	855	1	856	0.10%	Mode*
Child's Perception of Number of Neighbourhood Recreation Amenities	856	0	856	0.00%	NA

*based on attending-school averages
^PA = Physical Activity

Appendix D: List of Eligible Articles from Chapter 2 Rapid Review

1. Almanza, E., Jerrett, M., Dunton, G., Seto, E., & Ann Pentz, M. (2012). A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. Health and Place, 18(1), 46–54. https://doi.org/10.1016/j.healthplace.2011.09.003
2. Bondo, H., Demant, C., Toftager, M., Skau, C., & Schipperijn, J. (2015). Landscape and Urban Planning Objectively measured differences in physical activity in five types of schoolyard area. Landscape and Urban Planning, 134, 83–92. https://doi.org/10.1016/j.landurbplan.2014.10.005
3. Borghese, M. M., & Janssen, I. (2019). Duration and intensity of different types of physical activity among children aged 10–13 years. Canadian Journal of Public Health, 110(2), 178–186. https://doi.org/10.17269/s41997-018-0157-z
4. Bürgi, R., Tomatis, L., Murer, K., & De Bruin, E. D. (2016). Spatial physical activity patterns among primary school children living in neighbourhoods of varying socioeconomic status: A cross-sectional study using accelerometry and Global Positioning System. BMC Public Health, 16(1). https://doi.org/10.1186/s12889-016-2954-8
5. Bürgi, R., Tomatis, L., Murer, K., & De Bruin, E. D. (2015). Localization of physical activity in primary school children using accelerometry and global positioning system. PLoS ONE, 10(11). https://doi.org/10.1371/journal.pone.0142223
6. Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., … Sallis, J. F. (2015). Association between neighborhood walkability and GPS-measured walking, bicycling and vehicle time in adolescents. Health & Place, 32, 1–7. https://doi.org/10.1016/j.healthplace.2014.12.008
7. Carlson, J. A., Schipperijn, J., Kerr, J., Saelens, B. E., Natarajan, L., Frank, L. D., … Sallis, J. F. (2016). Locations of Physical Activity as Assessed by GPS in Young Adolescents. Pediatrics, 137(1). https://doi.org/10.1542/peds.2015-2430
8. Clevenger, K. A., Sinha, G., & Howe, C. A. (2019). Comparison of Methods for Analyzing Global Positioning System and Accelerometer Data during School Recess. Measurement in Physical Education and Exercise Science, 23(1), 58–68. https://doi.org/10.1080/1091367X.2018.1512495
9. Collins, P., Al-Nakeeb, Y., Nevill, A., & Lyons, M. (2012). The impact of the built environment on young people's physical activity patterns: Asuburban-rural comparison using GPS. International Journal of Environmental Research and Public Health, 9(9), 3030–3050. https://doi.org/10.3390/ijerph9093030
10. Collins, P., Al-Nakeeb, Y., & Lyons, M. (2015). Tracking the commute home from school utilizing GPS and heart rate monitoring: Establishing the contribution to free-living physical activity. Journal of Physical Activity & Health, 12(2), 155–162. https://doi.org/http://dx.doi.org/10.1123/jpah.2013-0048
11. Coombes, E., van Sluijs, E., & Jones, A. (2013). Is environmental setting associated with the intensity and duration of children's physical activity? Findings from the SPEEDY GPS study. Health and Place, 20, 62–65. https://doi.org/10.1016/j.healthplace.2012.11.008
12. Coombes, E., Jones, A., Cooper, A., & Page, A. (2017). Does home neighbourhood

supportiveness influence the location more than volume of adolescent's physical activity? An observational study using global positioning systems. The International Journal of Behavioral Nutrition and Physical Activity, 14, 9. https://doi.org/http://dx.doi.org/10.1186/s12966-017-0607-7

13. Cooper, A. R., Page, A. S., Wheeler, B. W., Griew, P., Davis, L., Hillsdon, M., & Jago, R. (2010). Mapping the walk to school using accelerometry combined with a global positioning system. American Journal of Preventive Medicine, 38(2), 178–183. https://doi.org/http://dx.doi.org/10.1016/j.amepre.2009.10.036
14. Cooper, A. R., Page, A. S., Wheeler, B. W., Hillsdon, M., Griew, P., & Jago, R. (2010). Patterns of GPS measured time outdoors after school and objective physical activity in English children: the PEACH project. INTERNATIONAL JOURNAL OF BEHAVIORAL NUTRITION AND PHYSICAL ACTIVITY, 7. https://doi.org/10.1186/1479-5868-7-31
15. Dessing, D., Pierik, F. H., Sterkenburg, R. P., van Dommelen, P., Maas, J., & de Vries, S. I. (2013). Schoolyard physical activity of 6-11 year old children assessed by GPS and accelerometry. International Journal of Behavioral Nutrition and Physical Activity, 10. https://doi.org/10.1186/1479-5868-10-97
16. Dunton, G. F., Almanza, E., Jerrett, M., Wolch, J., & Pentz, M. A. (2014). Neighborhood Park Use by Children. American Journal of Preventive Medicine, 46(2), 136–142. https://doi.org/10.1016/j.amepre.2013.10.009
17. Fjørtoft, I., Kristoffersen, B., & Sageie, J. (2009). Children in schoolyards: Tracking movement patterns and physical activity in schoolyards using global positioning system and heart rate monitoring. Landscape and Urban Planning, 93(3–4), 210–217. https://doi.org/10.1016/j.landurbplan.2009.07.008
18. Fjørtoft, I., Löfman, O., & Thorén, K. H. (2010). Schoolyard physical activity in 14-year-old adolescents assessed by mobile GPS and heart rate monitoring analysed by GIS. Scandinavian Journal of Public Health, 38(5_suppl), 28–37. https://doi.org/10.1177/1403494810384909
19. Gilliland, J., Maltby, M., Xu, X., Luginaah, I., Loebach, J., & Shah, T. (2019). Is active travel a breath of fresh air? Examining children's exposure to air pollution during the school commute. Spatial and Spatio-Temporal Epidemiology, 29, 51–57. https://doi.org/10.1016/j.sste.2019.02.004
20. Hecke, L. Van, Verhoeven, H., Clarys, P., Dyck, D. Van, Weghe, N. Van De, Baert, T., … Cauwenberg, J. Van. (2018). Factors related with public open space use among adolescents : a study using GPS and accelerometers, 1–16.
21. Jerrett, M., Almanza, E., Davies, M., Wolch, J., Dunton, G., Spruitj-Metz, D., & Pentz, M. A. (2013). Smart growth community design and physical activity in children. American Journal of Preventive Medicine, 45(4), 386–392. https://doi.org/http://dx.doi.org/10.1016/j.amepre.2013.05.010
22. Jones, A. P., Coombes, E. G., Griffin, S. J., & van Sluijs, E. M. F. (2009). Environmental supportiveness for physical activity in English schoolchildren: a study using Global Positioning Systems. INTERNATIONAL JOURNAL OF BEHAVIORAL NUTRITION AND PHYSICAL ACTIVITY, 6. https://doi.org/10.1186/1479-5868-6-42
23. Klinker, C. D., Schipperijn, J., Kerr, J., Ersbøll, A. K., & Troelsen, J. (2014). Context-specific outdoor time and physical activity among school-children across gender and age: Using

accelerometers and GPS to advance methods. Frontiers in Public Health, 2(MAR). https://doi.org/10.3389/fpubh.2014.00020

24. Klinker, C. D., Schipperijn, J., Christian, H., Kerr, J., Ersbøll, A. K., & Troelsen, J. (2014). Using accelerometers and global positioning system devices to assess gender and age differences in children's school, transport, leisure and home based physical activity. The International Journal of Behavioral Nutrition and Physical Activity, 11, 10. https://doi.org/http://dx.doi.org/10.1186/1479-5868-11-8
25. Lachowycz, K., Jones, A. P., Page, A. S., Wheeler, B. W., & Cooper, A. R. (2012). What can global positioning systems tell us about the contribution of different types of urban greenspace to children's physical activity? Health and Place, 18(3), 586–594. https://doi.org/10.1016/j.healthplace.2012.01.006
26. Lee, C., & Li, L. (2014). Demographic, physical activity, and route characteristics related to school transportation: An exploratory study. American Journal of Health Promotion, 28(3, Suppl), S77–S88. https://doi.org/http://dx.doi.org/10.4278/ajhp.130430-QUAN-211
27. Lee, N. C., Voss, C., Frazer, A. D., Hirsch, J. A., Mckay, H. A., & Winters, M. (2016). Does activity space size in fl uence physical activity levels of adolescents ? — A GPS study of an urban environment. Preventive Medicine Reports, 3, 75–78. https://doi.org/10.1016/j.pmedr.2015.12.002
28. Lin, Y., Borghese, M. M., & Janssen, I. (2018). Bi-directional association between sleep and outdoor active play among 10-13 year olds. BMC Public Health, 18(1). https://doi.org/10.1186/s12889-018-5122-5
29. McMinn, D., Oreskovic, N. M., Aitkenhead, M. J., Johnston, D. W., Murtagh, S., & Rowe, D. A. (2014). The physical environment and health-enhancing activity during the school commute: global positioning system, geographical information systems and accelerometry. GEOSPATIAL HEALTH, 8(2), 569–572. https://doi.org/10.4081/gh.2014.46
30. Maddison, R., Jiang, Y., Hoorn, S. Vander, Exeter, D., Mhurchu, C. N., & Dorey, E. (2016). Describing Patterns of Physical Activity in Adolescents Using Global Positioning Systems and Accelerometry. Pediatric Exercise Science, 22(3), 392–407. https://doi.org/10.1123/pes.22.3.392
31. Matisziw, T. C., Nilon, C. H., Wilhelm, S. A., Lemaster, J. W., Mcelroy, J. A., & Sayers, S. P. (2016). Landscape and Urban Planning The right space at the right time : The relationship between children ' s physical activity and land use / land cover. Landscape and Urban Planning, 151, 21–32. https://doi.org/10.1016/j.landurbplan.2016.03.006
32. Nethery, E., Mallach, G., Rainham, D., Goldberg, M. S., & Wheeler, A. J. (2014). Using Global Positioning Systems (GPS) and temperature data to generate time-activity classifications for estimating personal exposure in air monitoring studies: an automated method. ENVIRONMENTAL HEALTH, 13. https://doi.org/10.1186/1476-069X-13-33
33. Pearce, M., Saunders, D. H., Allison, P., & Turner, A. P. (2018). Indoor and Outdoor Context-Speci fi c Contributions to Early Adolescent Moderate to Vigorous Physical Activity as Measured by Combined Diary , Accelerometer , and GPS. Journal of Physical Activity and Health, (1), 40–45.
34. Pizarro, A. N., Schipperijn, J., Ribeiro, J. C., Figueiredo, A., Mota, J., & Santos, M. P.

(2017). Gender Differences in the Domain-Specific Contributions to Moderate-to-Vigorous Physical Activity, Accessed by GPS. Journal of Physical Activity & Health, 14(6), 474–478.

35. Pizarro, A. N., Schipperijn, J., Andersen, H. B., Ribeiro, J. C., Mota, J., & Santos, M. P. (2016). Active commuting to school in Portuguese adolescents: Using PALMS to detect trips. JOURNAL OF TRANSPORT & HEALTH, 3(3), 297–304. https://doi.org/10.1016/j.jth.2016.02.004
36. Quigg, R., Gray, A., Reeder, A. I., Holt, A., & Waters, D. L. (2010). Using accelerometers and GPS units to identify the proportion of daily physical activity located in parks with playgrounds in New Zealand children. Preventive Medicine, 50(5–6), 235–240. https://doi.org/10.1016/j.ypmed.2010.02.002
37. Rainham, D. G., Bates, C. J., Blanchard, C. M., Dummer, T. J., Kirk, S. F., & Shearer, C. L. (2012). Spatial Classification of Youth Physical Activity Patterns. American Journal of Preventive Medicine, (x), 1–10. https://doi.org/10.1016/j.amepre.2012.02.011
38. Remmers, T., Thijs, C., Ettema, D., de Vries, S., Slingerland, M., & Kremers, S. (2019). Critical Hours and Important Environments: Relationships between Afterschool Physical Activity and the Physical Environment Using GPS, GIS and Accelerometers in 10–12-Year-Old Children. International Journal of Environmental Research and Public Health, 16(17), 3116. https://doi.org/10.3390/ijerph16173116
39. Robinson, A., & Oreskovic, N. (2013). Comparing self-identified and census- defined neighborhoods among adolescents using GPS and accelerometer Comparing self-identified and census-defined neighborhoods among adolescents using GPS and accelerometer. International Journal of Health Geographics. https://doi.org/10.1186/1476-072X-12-57
40. Rodríguez, D. A., Cho, G.-H., Evenson, K. R., Conway, T. L., Cohen, D., Ghosh-Dastidar, B., … Lytle, L. A. (2012). Out and about: Association of the built environment with physical activity behaviors of adolescent females. Health and Place, 18(1), 55–62. https://doi.org/10.1016/j.healthplace.2011.08.020
41. Southward, E. F., Page, A. S., Wheeler, B. W., & Cooper, A. R. (2012). Contribution of the school journey to daily physical activity in children aged 11–12 years. American Journal of Preventive Medicine, 43(2), 201–204. https://doi.org/http://dx.doi.org/10.1016/j.amepre.2012.04.015
42. Stewart, T., Duncan, S., & Schipperijn, J. (2017). Adolescents who engage in active school transport are also more active in other contexts: A space-time investigation. Health & Place, 43, 25–32. https://doi.org/http://dx.doi.org/10.1016/j.healthplace.2016.11.009
43. Tarp, J., Andersen, L. B., & Østergaard, L. (2015). Quantification of underestimation of physical activity during cycling to school when using accelerometry. Journal of Physical Activity & Health, 12(5), 701–707. https://doi.org/http://dx.doi.org/10.1123/jpah.2013-0212
44. Taylor, L. G., Clark, A. F., Wilk, P., Button, B. L., & Gilliland, J. A. (2018). Exploring the Effect of Perceptions on Children ' s Physical Activity in Varying Geographic Contexts : Using a Structural Equation Modelling Approach to Examine a Cross-Sectional Dataset. Children, 5(159). https://doi.org/10.3390/children5120159
45. Van Kann, D. H. H., de Vries, S. I., Schipperijn, J., de Vries, N. K., Jansen, M. W. J., &

Kremers, S. P. J. (2016). Schoolyard Characteristics, Physical Activity, and Sedentary Behavior: Combining GPS and Accelerometry. Journal of School Health, 86(12), 913–921. https://doi.org/10.1111/josh.12459

46. Van Kann, D. H., Vries, S. I. De, Schipperijn, J., Vries, N. K. De, Jansen, M. W. J., & Kremers, S. P. J. (2017). A Multicomponent Schoolyard Intervention Targeting Children ' s Recess Physical Activity and Sedentary Behavior : Effects After 1 Year. Journal of Physical Activity and Health, 14, 866–875.
47. Voss, C., Winters, M., Frazer, A. D., & McKay, H. A. (2014). They go straight home - dont they? Using global positioning systems to assess adolescent school-travel patterns. JOURNAL OF TRANSPORT & HEALTH, 1(4, SI), 282–287. https://doi.org/10.1016/j.jth.2014.09.013
48. Ward, J. S., Duncan, J. S., Jarden, A., & Stewart, T. (2016). The impact of children's exposure to greenspace on physical activity, cognitive development, emotional wellbeing, and ability to appraise risk. Health and Place, 40, 44–50. https://doi.org/10.1016/j.healthplace.2016.04.015
49. Wheeler, B. W., Cooper, A. R., Page, A. S., & Jago, R. (2010). Greenspace and children's physical activity: A GPS/GIS analysis of the PEACH project. Preventive Medicine, 51(2), 148–152. https://doi.org/10.1016/j.ypmed.2010.06.001

Appendix E: Research Ethics Approval Forms for Use of Human Participants (redacted)

re-issued

Use of Human Participants - Ethics Approval Notice

Research Western

Principal Investigator: Dr. Jason Gilliland
Review Number: 17918S
Review Level: Delegated
Approved Local Adult Participants: 1200
Approved Local Minor Participants: 1200
Protocol Title: Identifying casual effects on the built environment on physical activity, diet, and obesity among children.
Department & Institution: Social Science\Geography, University of Western Ontario
Sponsor: Canadian Institutes of Health Research
Heart and Stroke Foundation of Canada

Ethics Approval Date: June 08, 2011 **Expiry Date:** August 31, 2014

Documents Reviewed & Approved & Documents Received for Information:

Document Name	Comments	Version Date
Other	Revised Healthy Neighbourhood Survey for Parents.	
Other	Revised Health Neighbourhoods Survey for Youth	
Other	Revised Activity and Travel Diary for School Days and Weekend Days.	

This is to notify you that The University of Western Ontario Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement: Ethical Conduct of Research Involving Humans and the applicable laws and regulations of Ontario has granted approval to the above referenced revision(s) or amendment(s) on the approval date noted above.

This approval shall remain valid until the expiry date noted above assuming timely and acceptable responses to the NMREB's periodic requests for surveillance and monitoring information.

[redacted] who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussions related to, nor vote on, such studies when they are presented to the NMREB.

The Chair of the NMREB is Dr. Riley Hinson. The NMREB is registered with the U.S. Department of [redacted] under the IRB registration [redacted]

[redacted]

Ethics Officer to Contact for Further Information

✓ Grace Kelly [redacted]	___ Janice Sutherland [redacted]

This is an official document. Please retain the original in your files.

The University of Western Ontario
Office of Research Ethics
Support Services Building Room 5150 • London, Ontario • CANADA - N6G 1G9
PH: 519-661-3036 • F: 519-850-2466 • ethics@uwo.ca • www.uwo.ca/research/ethics

Appendix F: Research Ethics Letter of Information for Parents (3 pages)

Western

Examining the Influence of the Neighbourhood Environment on Children's Health and Well-Being

Dear parent or guardian,

We would like to invite you and your child to participate in a study aimed at understanding how the neighbourhood environment around your child's school affects his or her health. The study involves grade 5, 6 and 7 classes at elementary schools across South Western Ontario.

What is being studied?
Our research team is studying the various places or facilities in their neighbourhood that children use (or intentionally don't use) on a regular basis for recreational or physical activities, including the way they travel to these places – for example, how they travel to and from school each day. We are also interested in looking at some of their eating patterns, especially the locations in their neighbourhoods where they might eat or purchase food. In addition, we'd like to learn more about how children feel about their local environments, and how this may affect the activities they do, or how and where they travel around their neighbourhood.

What will happen in this study?
If you and your child agree to participate in our project, **your child will be asked to:**

1. **Complete the *Healthy Neighbourhoods Survey for Youth*.** This survey primarily asks children about how they feel about their neighbourhood environments, the local facilities (such as parks) that they use for activities, places they may go to eat or buy food, and how they travel around their neighbourhood. Surveys usually take about 20-30 minutes to fill out and will be done in their classroom at a time decided by their teacher. (Note: students not filling out the survey will be given quiet activities by their teacher to do at their desks). Our research team will be on hand to help children fill out their surveys and to answer questions. All children will be given as much time as they need to complete the survey.

2. **Wear two small pieces of equipment each day during the hours they are awake, for two 7-day periods about 6 months apart – once during their Gr.5 or 6 year (Spring) and again in their Gr.6 or 7 year (in the Fall).** The lightweight 'GPS Logger', worn on a collapsible neck strap, maps out the general places the child visits in the neighbourhood and they routes taken to get from place to place. The tiny 'Accelerometer', worn on a thin elastic belt around the student's waist (can be worn under clothes), is like a pedometer that counts steps but it can also tell how 'intense' the activity of the student is. These tools will help us to see patterns in children's neighbourhood activities and travel. Because students will wear the tools during two different weeks we can also better understand how children's activities change over time.

3. **Complete a short activity diary for each day** they wear the 2 pieces of equipment, briefly telling us about their activities and any food purchases that day.

4. **OPTIONAL** – If they would like, participating students can also meet together with the researchers and classmates for a **group discussion** to talk more about how they feel about their neighbourhood and how their local environment helps or prevents them from enjoying the recreational activities they like, or easily buying the foods they want, or travelling easily around the neighbourhood. There will be about 10-20 students in a group. The discussion will take place either at lunch recess or outside school hours, and will last about 1 hour. It will be held at the school or another community location. Participation is completely voluntary; a child can decide not to join in the group discussion and still be allowed to join in Steps 1-3.

As the child's parent/guardian, **you will be asked to:**

1. **OPTIONAL - Complete the *Healthy Neighbourhoods Survey for Parents*.** The survey asks many of the same questions as the Youth survey, as well as questions about your home and family and your own feelings about your neighbourhood. It usually takes about 15-25 minutes to fill out. The Parent Survey is completely voluntary – your child can still join the study themselves even if you decide not to fill it out. However, it gives us valuable information from the point of view of parents so we would really appreciate your participation.

2. **OPTIONAL** - Parents of participating students will also have a chance to meet together with the researchers and other local parents for a **group discussion** about your neighbourhood environment and how it helps or prevents you and your family from doing the activities you like, buying the foods you need, or travelling easily around your neighbourhood. There will be about 8-12 parents in each group. The discussion will take place at a time outside school hours, and will last about 1-1.5 hours. It will be held at the school or another nearby community location. Participation in the group discussion is completely voluntary; a parent can decide not to participate and their child will still be allowed to participate in their own part of the study as outlined above.

Do we have to participate in this study?
Your participation in this study is completely voluntary. You and your child do not have to participate. You can each refuse to answer any survey questions, and can choose to leave the study at any time. Your decision will not affect your child's academic record in any way.

What are the benefits and risks if my child participates?
Recent research shows that our health is not only related to our personal lifestyle, such as the food we eat or physical activity we undertake, but also to the characteristics of the neighbourhood(s) we live in. This study will help us to better understand the links between our neighbourhoods, our activities, and our health. The results may help local municipal planners and school boards make decisions that will help plan healthier local communities.

There are no costs to you or your child for participating in this study. However, during each 7-day periods in which they participate, your child will receive $2 each day from the research team when your child hands in their completed activity diary for the previous day and data from their equipment is collected. Your child will receive an additional $1 on the last day when they return all their equipment. The total for EACH completed 7-day period is $15.

The equipment in this study is easy to use, and the researchers will spend time with your child to make sure they understand how to use and care for the equipment. But, if any pieces of equipment break or become lost during the time your child is using them, we will give them a replacement unit right away without any cost to you or your child.

There may be risks to your child if he/she participates in this study. Getting tired or becoming disinterested in continuing with the project for the full 7 days are considered the largest risks. However, each piece of equipment weighs less than 60g (0.12 pounds) and should not be difficult for a child to carry. And a child can decide to quit the project at any time. The height and weight of your child will also need to be measured before they start in order to properly set up the accelerometer. These measurements will be taken in a private room at the child's school in the presence of a trusted adult (e.g. school nurse or teacher); no other children or people outside of the research team will be present. The equipment used to measure a child's weight also has no visible display - the measurements are automatically sent wirelessly to a laptop and so will not be visible to either your child or anyone else in the room.

There is little risk that you or your child will be identified or identifiable in any of the documents related to the study. All of the information collected in this study is kept strictly confidential. You and your child will be assigned a unique identification code – your name or personal information will not appear on any materials or data files. Also, materials and data files will ONLY be viewed by members of the research team and will be stored in a locked filing cabinet or on a password protected computer in a secure room at the University of Western Ontario. Parents and children who participate in the group discussions will be asked to keep everything they hear confidential and not to discuss it outside of the meeting. However, we cannot guarantee that confidentiality will be maintained by other participants in the focus group. Children can ask to see the maps of their own travel patterns and to change any information that feel is incorrect. However, to protect the privacy of each child, parents will not be able to view children's data or maps.

If you or your child decides to leave the study at any time (even up to 30 days AFTER the study has been completed), any of personal data collected from you or your child will be immediately destroyed and excluded from the study analysis.

You do not waive any of the legal rights you would otherwise have as a participant in a research study.

Follow Up
As the study involves a second round of participation this coming Fall (approximately 6 months after the first round this Spring), we may need to contact you at your home by phone or email in order to find out if your child changed schools between Spring and Fall. **We would therefore ask that you include one or both of these pieces of information on the attached consent form.**

Who do I contact if I have any other questions?
Should you have any questions or concerns about participating in this project, you can contact the lead researcher, Dr. Jason Gilliland, at the University of Western Ontario. [redacted] or email: [redacted]

If you have any further questions regarding your rights as a study participant, please contact the Office of Research Ethics at [redacted] r at: [redacted]

Research Team
Dr. Jason Gilliland, Department of Geography, University of Western Ontario
Dr. William Avison, Department of Sociology, University of Western Ontario
Dr. Harry Prapavessis, Department of Health and Rehabilitation Sciences, University of Western Ontario
Dr. Paul Hess, Department of Geography and Planning, University of Toronto
Dr. Kathy Speechley, Department of Paediatrics, University of Western Ontario
Dr. Piotr Wilk, Department of Epidemiology, University of Western Ontario
Dr. Colleen Gobert, Division of Food & Nutrition Sciences, Brescia University College
Mr. John Fleming, Director of Planning, City of London

This letter is for you to keep. Please return the attached Parent/Guardian consent form. You will also be given a copy of this consent form once it has been signed.

Appendix G: Research Ethics Parent Consent Form

Western

Examining the Influence of the Neighbourhood Environment on Children's Health and Well-Being

Parent / Guardian Consent Form

<u>Regardless</u> of whether you are consenting to let your child to participate in this study, we would ask that you return this form to school with your child, sealed in the envelope provided. Envelopes will be collected by your child's teacher. Thank you!

Consent: I, ____________________________ ***(name of parent/guardian- please print)***, have read this letter and have been given the opportunity to ask questions. Any questions I had have been answered to my satisfaction. (Check all boxes that apply):

☐ I agree to participate by completing the *Healthy Neighbourhoods Survey for Parents* (***optional****; if yes, please seal the survey in the envelope provided and return <u>with</u> signed consent form*)

☐ I am interested in being contacted about participating in a group discussion for parents (***optional;*** *if yes, please provide either phone or email contact information below)*

Please select one of the following 2 options:

☐ I agree to let my child ________________________________ ***(child's full name – please print)*** participate in the full 14 days (two 7-day periods within the next 6-8 months) of the project as outlined. ***REQUIRED: My child <u>has</u> health issues which restrict their ability to walk/exercise or otherwise participate in this study*** ☐ ***YES*** ☐ ***NO***

<u>OR</u> if your child is not interested in the full project but would still like to participate in the survey

☐ I agree to let my child _________________________________ ***(child's full name – please print)*** participate **ONLY** by way of completing the *Healthy Neighbourhoods Survey for Youth* (to be administered at child's school) rather than the full study.

___________________________________ ___________________________________

Parent / Guardian's signature Date

If your child IS participating, please provide a phone and/or email address (both is preferable) so that we may contact you this Fall to confirm whether or not your child has changed schools since the Spring. This information will be kept strictly confidential.

___________________________________ ___________________________________

Parent/Guardian Email Address Home or Cell Phone

Appendix H: Research Ethics Child Assent Form

Western

How Healthy is the Environment in Your Neighbourhood?

Hello! We are researchers from the University of Western Ontario and we are doing a study in your neighbourhood! We need students in Grades 6, like you, to help us with this project!

What are we going to study?

We all know that getting lots of exercise and eating the right foods can help keep us healthy. We'd like to know if the places or services that you have and use in your neighbourhood also help to keep you healthy.

What would you have to do?

If you agree to be in the study there are 4 things we would like you to do:

Equipment looks like this!

1. Wear 2 small pieces of equipment every day for a week this Spring. A small GPS unit will help to make a map of all the places you visit every day. You would also wear a 'loonie'-sized piece of equipment on an elastic band around your waist that will tell us when you are doing physical activity, like running or playing sports. Both pieces of equipment are very light and easy to use. We will also come to your school every day in case you need help.
2. Fill out a short 1-page diary everyday about the activities you did that day.
3. Fill out a short survey on what you think about your neighbourhood. You will fill this out one day at school with your classmates. It takes about 20-30 minutes to finish but you can take as much time as you need.
4. Then you would wear the equipment and fill out the diary again for a week later this Fall when you are in grade 7 (even if you are then going to a different school).

After both weeks are done, you could also join in a group discussion with some of your classmates to talk to us about where you like to go in your neighbourhood and the activities you like to do. You do not have to join in this group activity. The talk will take place at your school. We would like to audio record our talk.

To work some of the equipment we'll need to measure your height and weight. We'll do this in a private room at your school. Your teacher can be in the room. We won't share the information with anyone else.

Do you have to join this project?

No – you will only join if you would like to. You can also decide at any time that you would like to stop. We will never share your information with anyone else, even your parents, but you can ask to see it at any time. You can ALWAYS talk to your teacher or the researchers if you have any questions or worries.

I want to participate in this study!

If you would like to join this study in some way, choose one of the following two options:

☐ I want to participate in the full 2 week study **OR** ☐ I only want to complete the in-class survey

____
Print First and Last Name of Child

___________________________________ _____________ ______________________
Signature of Child Age of Child Date

___________________________________ ______________________
Signature of Person Obtaining Assent Date

Curriculum Vitae

Name:	Malcolm K. Little
Post-secondary Education and Degrees:	The University of Western Ontario London, Ontario, Canada Sept 2018 - Dec 2020 (expected) M.Sc. Kwantlen Polytechnic University Surrey, British Columbia, Canada 2010-2016 B.A. (Hons) *with distinction*
Honours and Awards:	Social Science and Humanities Research Council (SSHRC) Canada Graduate Scholarship – Master's 2019-2020 Ontario Graduate Scholarship 2018 – 2019 The University of Saskatchewan Dean's Scholarship 2018-2019 (declined) ESRI Young Scholars Award 2016
Related Work Experience:	Research Assistant Human Environments Analysis Laboratory 2019 – present Teaching Assistant The University of Western Ontario 2018 – 2020 Data/Systems Consultant DataTech Mainland Ltd. 2015 – 2018 Research Associate Kwantlen Polytechnic University 2010 – 2016
Conference Presentations:	GIS in Education and Research Conference (ESRI) 2020 Toronto, Ontario *"A Child's Space-Time Continuum? Spatiotemporal Analysis of How Children Use Their Neighbourhoods"*

Canadian Association of Geographers 2019
Guelph, Ontario
"A Child's Space-Time Continuum? Spatiotemporal Analysis of How Children Use Their Neighbourhoods"

GIS Day @ Western University 2018
London, Ontario
Lightning Talk

GIS Day @ Western University 2019
London, Ontario
Lightning Talk

GIS Day @ Western University 2020
London, Ontario
Lightning Talk

Publications:

Wray, A., Martin, G., Ostermeier, E., Medeiros, A., Little, M., Reilly, K., & Gilliland, J. (2020). Physical activity and social connectedness interventions in outdoor spaces among children and youth: A rapid review. *Health Promotion and Chronic Disease Prevention in Canada*, 40(4), 104–115. https://doi.org/10.24095/hpcdp.40.4.02

Little, Malcolm & Peplow, Stephen. (2017). A Validation of England's Nineteenth Century Tithe Files, Using GIS as a Primary Tool. *International Journal of Humanities and Arts Computing*, 13. 1-32. 10.3366/ijhac.2017.0186.

Venditti, J. G., Rennie, C. D., Bomhof, J., Bradley, R. W., Little, M., & Church, M. (2014). Flow in bedrock canyons. *Nature*, 513(7519), 534–537. https://doi.org/10.1038/nature13779