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The Local Food Environment of Children in London Ontario: A Methodological Comparison

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

THE LOCAL FOOD ENVIRONMENT OF CHILDREN IN LONDON ONTARIO: A METHODOLOGICAL COMPARISON

(Thesis format: Monograph)

by

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Abstract

The present study examined current methodological approaches to characterize the local food environment around children in London, Ontario, assessing variations in BMI and dietary preferences in relation to the choice of food environment measure. Taking advantage of a unique dataset that collected GPS trajectories of children's schools and homes for a large sample of children between 11 and 14 years of age, two commonly-used approaches (i.e., network buffers and Euclidean buffers), and two novel measures of activity spaces (i.e., standard deviational ellipses and α-hulls) are used as 'geographic containers' (i.e., areal units) to derive food outlet measures. Results showed slight to low agreement in the percent of shared area between the various containers and the α-hulls. Kappa statistics further confirmed the slight to low agreement between the food outlet measures derived from activity space containers and Network and Euclidean buffer containers. There is considerable variation in the maximum number of outlets between the various group comparisons across gender, weight status and reported food outlet visit. In addition, results from logistic models point to consistent evidence of gender differences in dietary and weight outcomes across containers, but did not support an overall clear effect of food environment measures across choice of geographic container.

When assessing the role of local food environment on children's outcomes, studies should select the appropriate geographic container definition depending on whether the focus is on opportunities (accessibility) or affordances (exposure).

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Chapter One: Introduction

1.1. General Introduction

For the past two decades, research seeking to discern the links between the built environment and individual outcomes has increased substantially, giving way to important methodological and theoretical contributions. Individual outcomes for physical activity, commuting, leisure and eating are increasingly seen as dependent upon the opportunities and barriers of the local environments where people live, work and play. In particular, a steep population shift in obesity incidence, thought to be associated with equally significant population- wide changes in both the level of physical activity and eating behaviours, has brought built environment studies front and center.

Although causal pathways to obesity are complex and involve genetic, individual, and contextual factors driving both energy expenditure and energy intake, there is overall consensus about the independent role of the built environment on health outcomes, either directly or indirectly. More specifically, previous literature provides robust evidence that there are environmental influences on energy balance behaviours. (Kremers et al., 2006).

Previous studies have provided evidence that among children, food stores constitute the largest source of energy for foods eaten away from home (Poti & Popkin, 2011), and that a higher proportion of children in Canada report buying their school lunch at a convenience store or fast-food restaurant or cafes than children in the US or Scotland. (Héroux et al., 2012). Taking this evidence, along with recent research stating that the excess intake of high sugar, high fat foods surpassed the amount of under consumption of fruits and vegetables (Cohen et al., 2010), and that fruit and vegetable consumption has a significant effect on BMI –for the Canadian context- (Azagba & Sharaf, 2012), underscores the relevance of evaluating children's local food environment, as it is a likely source for unhealthy foods.

Several literature reviews on the link between food environment and individual health and diet outcomes generally show support for the relationship of the presence of restaurants and supermarkets and healthier dietary outcomes. However, they point to the inability to discern causal links due to issues such as the Modifiable Areal Unit Problem –MAUP- (Kwan, 2012) or self-reported data, as well as the complexity of the pathways leading to obesity that include genetics, physical activity levels and cultural and social factors.

While a large number of studies on the topic provide empirical evidence for the link between where people live and what they eat, overall agreement has not been reached. A likely source of such mixed results between studies is the variation in how we define and measure the food environment, both in terms of scale and geographic units. Ball and colleagues (Ball, Timperio, & Crawford, 2006) noted the need to identify true environments in determining the effect of built environment on individual outcomes. The authors also acknowledge the difficulty of such a task given that people are not bound to a pre-defined view of their neighbourhood and more often than not they move between different contexts or domains.

Given that replicability is key to assessing whether a proposed association, i.e. food environment and obesity, is robust to the choice of neighbourhood or food outlet measurement, more studies including multiple measures and approaches are essential to overcome the inconclusive evidence. This is particularly true for studies looking at children, since to date, they remain a small share of the food environment literature (Odoms-Young et al., 2012).

1.2. Study Objectives

The present study seeks to contribute to the literature by assessing children's local food environments. The purpose of this study is twofold: a) to identify and critically examine different methods for defining children's neighbourhood food environments (i.e., outside the home); and b) to characterize the local food environment around a sample of children in London, Ontario examining variations in BMI and dietary preferences in relation to the choice of food environment measure. To do this, two commonly-used measures (i.e., network buffers and Euclidean buffers), and two novel measures of activity spaces (i.e., standard deviational ellipses and α-hulls), will be used as 'geographic containers' (i.e., areal units) to derive food outlet measures. The study takes advantage of a unique multi-year multi-method project that collected GPS trajectories around children's schools and homes for a large sample of children between 11 and 14 years of age.

The analysis presented here seeks to answer the following research questions:

1. How does the choice of geographic container influence the food environment measures derived for convenience stores, fast-food restaurants, restaurants and supermarkets?

2. To what degree do geographic containers used in the literature to represent children's local environments accurately capture their actual use of space?

3. How is the local food environment structured around children across London, Ontario?

1.3. Contribution to the Literature

This study contributes to the body of research on the built environment and children's outcomes in two respects. First, most studies focus on an individual's residential address to derive their food environment either through administrative areas such as postal codes or by way of Euclidean or street network buffers within a threshold distance of their residential address. Yet, children spend considerable time outside their homes, with previous research indicating that they are out of their home around 38 percent of the time –with seasonal variation (Oreskovic et al., 2012). The present study utilizes GPS data to derive ego-centric local neighbourhoods that are not restricted to the home address and can provide insights into the way children navigate geographic space. Second, to date, most studies on food environment and children include one or two definitions of the local food environment, providing limited evidence of the role and the degree of differences between geographic containers. The present study includes four different containers of several sizes for a large sample of children, allowing robust comparisons between the most commonly found approaches to local food environments in the literature.

1.4. Organization of the Study

This document consists of seven chapters including this introduction. *Chapter two* provides a detailed systematic review of the literature published after 2008 which specifically looks at GIS-based analyses to study the food environment. *Chapter three* discusses conceptual approaches to define and measure the food environment, which guide the present methodological comparison analysis. *Chapter four* describes the data sources and methodology used in this study. *Chapter five* presents the results of the comparative analysis that include the four types of geographic containers and their various distance parameters. *Chapter six* describes the results of the analysis of the association between the local food environment and children's health outcomes (i.e., BMI), separately by food outlet and geographic container. Finally, *Chapter seven* presents the discussion, conclusion and limitations of the present study.

Chapter Two: Review of the Literature

2.1. Highlights from Previous Food Environment Literature Reviews

We looked at literature reviews on food environment published after 2008 to serve as a starting point of the systematic literature review that is presented in the following section. The literature still lacks consistency regarding which characteristics of people's local food environment can have a significant impact on health-related issues such as BMI or obesity prevalence. While some studies have found evidence that availability of healthy foods, as represented by access to grocery stores or supermarkets, can lead to better diet choices, other studies point to fast-food and not grocery stores as being significantly related to individual outcomes.

To assess the impact of the built environment on health outcomes it is necessary to define spatially what represents the local neighbourhood or local environment. Surprisingly, the bulk of studies deal with how the built environment influences outcomes, while only a few studies focus on how to appropriately define and measure the built environment, and how health outcomes might be affected by the way we define and measure what constitutes the local food environment; in other words, the choice of 'geographic container' is given little attention in previous studies.

Most of the studies included in this literature review point to an association between obesity or eating behaviours and some aspect of the built environment, although several gaps remain. Regarding context, the bulk of the studies focus on the US and the few Canadian studies that do exist focus mostly on large cities or metropolitan areas.   Empirical studies on the food environment and children have been mostly concerned with the school food environment through the use of buffer zones around schools or pre-existing administrative areas such as census tracts or zip codes.

Feng et al. (2010) looked at 63 eligible papers using either administrative areas or home-based geographic buffers to analyze the effect of the built environment on weight outcomes. They noted a great degree of heterogeneity in the shape, measure and spatial scale of the built environment used. The authors reported that over half of the relations in the studies using administrative areas and less than half of the relations in the studies using buffers turned out to be significant. However, the review concludes that methodological differences prevent any systematic comparison and calls for further research providing grounds for agreement on the role of the built environment, with particular attention to the influence of the choice of metrics and the definition of place that still remains a "black box" in health and place research.

Charreire (2010) reviewed food environment studies using GIS methods. The authors noted that density and proximity were the two key concepts used to evaluate the food environment, with eighteen out of twenty nine of the studies reviewed using food outlet counts based on circular or network buffers. Caspi (2012) reviewed 38 articles specifically looking at food environment exposure methods and diet outcomes. The majority of the studies employed a GIS approach, with some studies including non-spatial methods looking at affordability, in-store food content and quality. Seven out of 13 studies found no significant associations between distance to food stores and diet outcomes and two found mixed results. However, studies focusing on perceived measures of accessibility found empirical support for an effect on diet. The authors conclude that the inconsistency across studies can be related to the how well the GIS boundaries employed reflect a resident's neighbourhood, as well as to the quality of secondary food data sources broadly used. They recommend ground-truthing food databases to avoid wrong accessibility measures from use of outdated food locations and explore alternative spatial measures of the food environment such as kernel density or travel time. They recommend integrating information on the type of food outlet (the community nutrition environment) and food products within them (the consumer nutrition environment), along with avoiding over-simplification of food outlet categories and including alternative outlets such as gas stations and pharmacies as they also provide access to various food items.

Kelly et al. (2011) present a systematic literature review on methods used to measure the food environment, based on 63 articles. They find density and proximity are the two most common measures of the food environment, and standard commercial definitions (i.e., NAICS code for supermarket, convenience, grocery, fast-food restaurant), relative indexes (i.e., RFEI and dichotomous healthy/unhealthy categories) are the most common food outlet classifications used across studies.

Also, Gustafson et al. (2012) reviewed the consumer food environment, looking only at studies analyzing the food content found within food stores. The authors highlight the broad number of food audit tools which prevent adequate comparison across studies. This is likely the factor behind the mixed results across studies on the association of available fruit and vegetables, healthy or unhealthy snacks and consumption or BMI. Also, they point out only few studies provided information on whether individuals prefer shopping at nearby outlets, although those that did reported most people do rank proximity to home as the main criteria in selecting their food store.

In another review by Leal & Chaix (2011), which looked at longitudinal studies on environmental correlates of cardio-metabolic risk factors, over 70 percent of the selected studies used predefined areas to measure the environment and 26 percent used buffers that were in turn, mostly Euclidean-based buffers. With regards to food outlets, they found that only 9 out of 20 studies reported statistically significant associations with weight (Leal & Chaix, 2011). They identify the appropriate definition of a neighbourhood as a challenge, and recommend sensitivity analyses that take into account the effect of different neighbourhood criteria on outcomes. They also highlight the need to include alternative definitions of the built environment other than those based on residential home address.

2.2. Systematic Literature Review of Current Food Environment Literature

2.2.1. Description of the Review

A systematic literature review was conducted as a first step, to gain insight into the methodological approaches used to define the local food environment.

Peer-reviewed journal articles written in English and published after 2008 were obtained from literature searches using PubMed, Scopus and GEOBASE databases using the food environment keywords: *"food environment", "food desert", "food retail", "food access", supermarket, restaurant*, "grocery store", "convenience store", foodscape, obesog**, or *"food outlet"*, in conjunction with the geographic keywords: *"urban form", "built environment", "built form", geography, "land use", GIS, "Geographic Information System"* or *map**. The initial search yielded 160 articles in GEOBASE, 22 articles in PubMed and 464 in Scopus.

Journal articles that did not meet the following criteria were excluded from further review: a) it is concerned with the food environment outside the home or school realm; b) it is not an intervention study, a simulation study, or a literature review; and c) it explicitly uses GIS to define and derive a geographic container to represent the local food environment. A total of 99 papers were eligible for in-depth screening, and after excluding papers that did not approach the food environment using GIS, a total number of 77 articles were included in the review table.

The literature presented in Appendix A is a clear representation of the current and latest approaches to define and measure the food environment through the use of Geographic Information Systems. Studies prior to 2008 were not included since they have been reviewed elsewhere (Charreire et al., 2010). Of the 77 papers (since 2008) reviewed in-depth, more than half of the studies came from the U.S. (51 studies), but there are also several studies relevant to the Canadian context (13 studies), and a smaller number for other contexts such as U.K. France, Australia, New Zealand and Denmark.

2.2.2. Characterization of the Food Environments in the Reviewed Studies

Network buffers or distance was the most common approach to define the local food environment (33 studies), followed by Euclidean-based measures (25 studies) and administrative/census definitions (21 studies). Far less common were studies employing ego-centric definitions of the local food environment, with only 5 studies using activity spaces, 3 studies using Kernel Density and 3 studies using grid-based approaches (see

Figure 1).

Although the majority of the reviewed papers used different container sizes ranging from 400 meters to 2 kilometres when employing address-based buffers, only 20 percent (15 studies) of the reviewed papers used more than one type of geographic container. Interestingly, studies with a child or adolescent target population most often use residentially-based measures with only 1 study using activity spaces to define children's local neighbourhood.

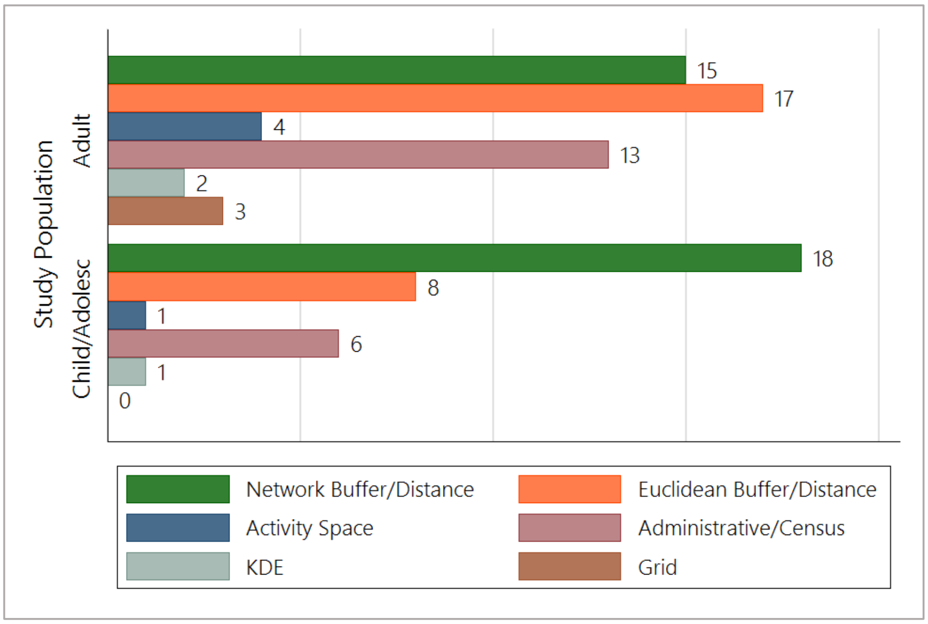

Figure 1. Number of Studies Reviewed by Geographic Container Used to Measure the Food Environment and Study Population

Figure 2 shows the type of measure used to assess the food environment in the studies reviewed, with density or counts being the most prominent measure reported in the methodology. Other measures included distance or time to nearest food outlet, presence or absence of food outlet in the local environment, and other less common measures such as food environment index (e.g., RFEI [Retail Food Environment Index]), linear shelf space and spatial clustering coefficient, although they were reported mostly on adult-based studies.

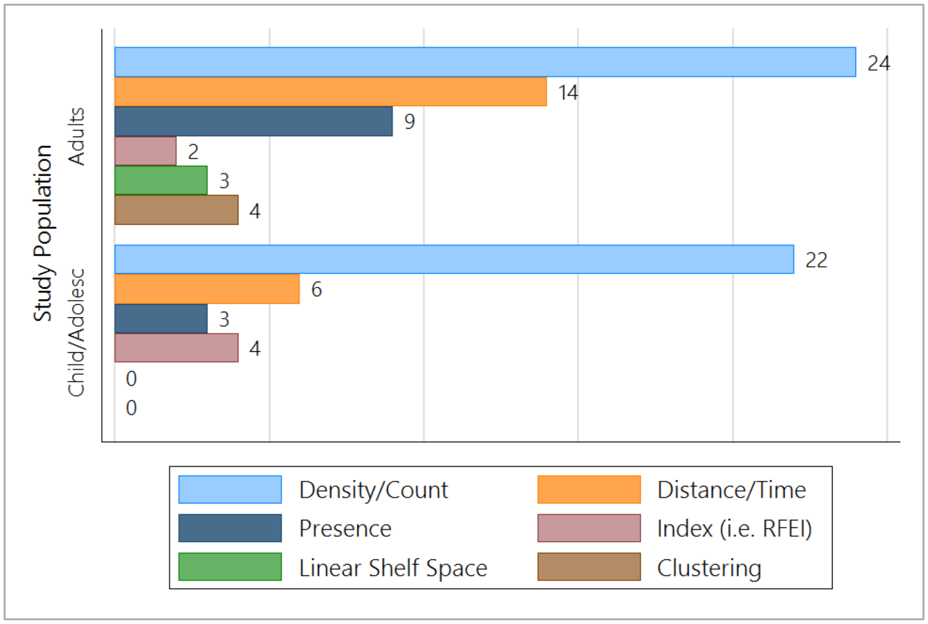

Figure 2. Food Environment Measure by Study Population (Number of Times Used in Previous Studies)

In terms of the type of food outlet used to characterize the food environment, Figure 3 shows that most studies utilize the commonly used categories: fast-food restaurants, full service restaurants, convenience stores, supermarkets and/or grocery stores. However, some studies were interested generally in food shopping locations or healthy vs. unhealthy food outlets, while others used more nuanced classifications by using specific categories such as coffee shops, pizza places, bakeries or specialty food outlets, or restricting outlet classification to definitions such as national chain supermarkets, fast-food restaurants selling specific food items, or grocery stores reporting specific revenue thresholds.

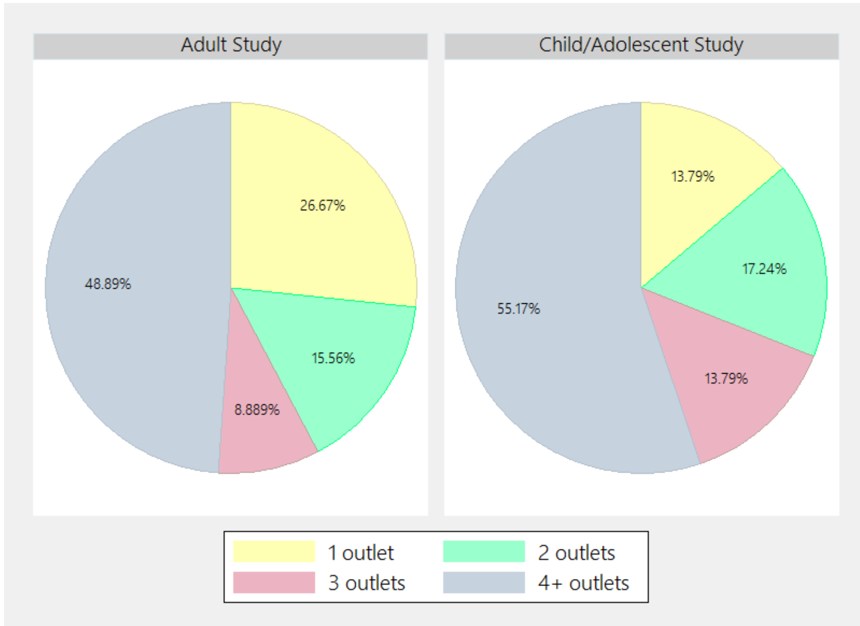

Figure 3. Types of Food Outlets by Study Population Used in the Literature

2.2.3. Empirical Evidence -Highlights by Geographic Container

The studies reviewed bring important methodological and empirical contributions to the literature on food environment and health. Overall, studies including multiple geographic containers observe significant differences in the food environment measures derived from them, and even some noted the superiority of ego-centric based containers. Still, the empirical evidence provided failed to reach agreement on the significance and magnitude across geographic containers.

Thornton et al. (2012b) used road network proximity, Euclidean and network buffer counts and kernel density to analyze the effect of supermarkets on fruit and vegetable consumption in Glasgow, Scotland and found the strongest associations for the kernel density method and inconsistent results for other geographic containers.

Boruff et al. (2012) looked at different buffering techniques to define the local neighbourhood from which built environment measures are to be derived and their effect on walking. The authors included standard Euclidean and network based buffers as well as alternative convex hull, ellipses and central road alternatives derived from three types of facilities around residential addresses. Out of all buffers, the facility-based convex hull and ellipse had better goodness of fit.

Kestens et al. (2012) included administrative neighbourhood and activity space geographic containers and found the latter to explain more between neighbourhood overweight variance than the former for males while the opposite was observed for females. However, they used different datasets to derive the food environment and health outcomes assuming both samples were similar based on geographic and time scopes.

Kestens et al. (2010a) used two kernel density estimation measures for home and activity space and found wide variations for the different food outlet densities between these two geographic containers, along with variations for age and income groups, although their study is based on data collected for one day to derive activity spaces. Seliske et al. (2012) used a network buffer geographic container for 500 m, 750 m, and 1000 m, and found the latter to yield the best fit, although their analysis is based on the assumption that students reporting eating outside school, do so at a nearby outlet, an assumption broadly found on the literature. Conversely, in a study in Montreal and Quebec, Lebel et al. (2012), found that although activity spaces were significantly associated with overweight status for men and not women, administrative neighbourhood containers explained more place based variation.

Zenk et al. (2011) also used different geographic containers to evaluate the effect of supermarket and fast-food outlets on diet and physical activity among network buffers, SD ellipse activity space and daily path activity space (both GPS derived). The authors found the activity space but not the network container to be related with dietary intake. More importantly, they highlight that an individual's movement reflects a broader space than that of their residential neighbourhood, although their study reports a small sample size with data collected during winter time, which may compromise representativeness of the activity space. This is also observed by Nelson et al. (2010) in their study of eating (out of home) and purchasing behaviours, with only 12 percent of either occurring within half a mile of their home, and an average distance of about 7 miles for eating trips and 3 miles for shopping trips.

Christian (2012) also compared the effect of activity spaces and census tract derived food outlet measures on food consumption and weight outcomes for a sample of adults, finding significant differences between both containers, with activity spaces being over four times larger than census tracts; with activity spaces obtained from three days of data collection on a single census tract. Additionally, Villanueva (2012) compared network and travel survey derived activity spaces for a sample of Australian children and noted that more than half of them used less than 25 percent of the 800 m and 1600 m network geographic container, with gender, distance to busy roads, mobility and number of local destinations related to the size of activity spaces.

2.2.4. Empirical Evidence -Highlights by Type of Food Outlet

As it is the case with geographic containers, the reviewed literature is characterized by a lack of consistency in the significance, magnitude and direction of food environment influences on individual outcomes by type of food outlet, with studies that found no impact of food outlets, studies presenting robust evidence that the local food environment plays a role, and studies yielding mixed evidence, usually those including multiple food outlets, geographic containers or outcomes.

The reviewed studies followed common criteria to define food outlets. Fast-food outlets are characterized by limited-service, with most offering short waiting times, and limited simple menu items, with those belonging to national chain outlets being easily identifiable. Full service restaurants on the other hand, generally have dine-in arrangements, full entree menus and longer waiting times. As it is standard in previous literature, the reviewed studies have used local directories, expert knowledge, or industrial classifications such as the SIC or NAICS to categorize restaurants as fast-food or full service restaurants. It is worth noting that the wide range of empirical results may be related to the way that food outlets are classified. As an example, most food environment studies equate supermarkets with healthy food outlets given the availability of fresh produce. However, and particularly for children, supermarkets are often also places where they can access unhealthy foods such as cookies, soda, or chips.

Among the studies reviewed, several used a longitudinal approach. Shier and Strum (2012) found that the cross-sectional significance of food outlets on children's BMI did not remain in longitudinal models. Similar results were reported by Lee et al. (2012) with no significant effect of food outlet exposure on weight gain over time, using a census tract container on a US national sample dataset. Block et al. (2011) found a negative effect of increased distance to the closest fast-food restaurant on BMI only for women, using time-varying individual data. Additionally, Boone-Heinonen et al. (2011) using longitudinal measures of food consumption found no effect of supermarket and only a significant effect of fast-food restaurants in one of the four Euclidean geographic containers for low income men.

Other cross-sectional studies also found no significant effect of food environment on outcomes. An & Sturm (2012) found no relationship between food consumption and each of the food outlets within three different Euclidean buffers. Seliske et al. (2009) found no association of different food outlets and a food retailer index around school and children's overweight. Shaw (2012) concluded that SES was a stronger predictor of obesity and fruit/vegetable intake than fresh food retailers. Ford et al. (2011) showed that the presence of supermarkets or other retail food stores did not mediate the relationship between deprivation and BMI. Harris et al. (2011) failed to find empirical support for the effect of different food outlets on adolescents' BMI using network based geographic containers for proximity and count measures.

One of the few studies that included multiple health outcomes from a sample of women in a national study found that food environment measures display a more consistent relationship with BMI and obesity than with blood pressure and hypertension outcomes, and provide support for the expected positive effect of fast-food outlet density and negative effect of grocery stores and supermarket density on both outcomes.

Several of the studies included in this review dealt with the specific topic of food deserts, with some studies providing empirical support for differential access to healthier food outlets for low income areas (Richardson et al., 2012). Still, other studies found no significant evidence, while some found support for 'food swamps' instead, whereby excess unhealthy food outlets rather than lack of healthy ones are overrepresented in deprived areas (Eckert & Shetty, 2011; Lee, 2012; Leete, Bania, & Sparks-Ibanga, 2011; Russell & Heidkamp, 2011; Svastisalee et al., 2011), and yet other studies found the opposite trend with higher distances from supermarkets for high income areas, as it is the case of the study by Rosenshein and Waters (2009).

2.2.4.1. Fast-food Restaurants

Fast-food restaurants have received considerable attention in public health studies related to eating behaviours or preferences. This is likely so, given the evidence about the increase participation of restaurants as a source of food purchases, coupled with the increase in portion sizes and higher calorie intake compare to home prepared meals. (Austin et al., 2005; Finkelstein et al., 2010; Story et al., 2008). For children in particular, the share of restaurants in the energy intake of youth has been reported to increase by 300 percent between the 1970s to the 1990s (St-Onge et al., 2003). Additionally, more recent evidence points to the role of fast-food and full service restaurant consumption and increase total energy intake, soda and sugar-sweetened drink intake, total fat, saturated fat and sugars for children and adolescents (Powell & Nguyen, 2013). Moreover, there is empirical evidence about the ubiquitous presence of fast-food restaurants near schools in the US and Canada (Austin et al., 2005b; He, Tucker, Gilliland, et al., 2012), which is concerning given that children who consume fast-food have a higher calorie intake than those who do not (Paeratakul et al., 2003).

Following the trend in previous reviews, a considerable number of the studies reviewed here found fast-food restaurants to play an important role on various individual outcomes. Gordon et al. (2011) provided empirical evidence for the relationship between visits to fast food outlets and higher soda intake, up to a 20 percent increase. Brennan and Carpenter (2009) found statistically significant associations between higher number of fast-food restaurants within half a mile (Euclidean distance) of schools and children's lower fruit and vegetable intake, higher soda intake, and higher BMI; these results have been supported by the study of and Sanchez et al. (2012) for the same geographical context (California). Fast-food outlets were also significantly associated with BMI and fast-food consumption among adolescents in the U.K. (Fraser et al., 2012). Several studies found similar trends regarding the significant effect of fast-food restaurants on BMI (Lamichhane et al., 2012). Mercille et al. (2012) also found a negative and significant effect of fast-food outlets on a sample of Montreal seniors' dietary patterns using a network based geographic container. Another Canadian study, looking particularly at children found that students with more than 3 food outlets within a 1000 m, more than 2 outlets within a 750 m, and more than 1 outlet within a 500 m network buffer, have greater odds to eat lunch at a food outlet outside school (L. Seliske et al., 2012). Similar results were found for a sample of children in London, Ontario, Canada regarding fast-food and convenience stores and food purchasing and food consumption (He, Tucker, Gilliland, et al., 2012; He, Tucker, Irwin, et al., 2012). Heroux et al. (2012) included participants from Canada, the U.S., and Scotland, and found a higher proportion of the U.S. participants to be overweight or obese compared to those from Canada or Scotland, but a higher proportion of Canadian participants ate lunch at a snack bar, fast-food restaurant, or cafe compared to participants in the United States. Forsyth et al. (2012) observed that Black, Hispanic, and Native American adolescents, live in areas with more fast-food outlets and reported a higher frequency of eating at these outlets relative to White and Asian adolescents. Additionally, Day and Pearce (2011) noted that New Zealand schools have five times the amount of fast-food outlets nearby than expected based on a planar multi-type K-function, with schools in the lower SES quintile having three times as many outlets as those in the highest quintile, and primary and middle schools having a higher proportion of fast-food outlets than secondary school. Conversely, Casey et al. (2012) found no significant effect of fast-food or bakeries within 1000 m Euclidean geographic container on children's overweight, and Ellaway et al. (2012) found no evidence of clustering for different food outlets around schools using also Euclidean buffer of different sizes.

2.2.4.2. Convenience Stores and Supermarkets

Previous literature has also highlighted the difference in diet quality between supermarkets and grocery stores and smaller corner or convenience stores, with the former thought to provide more choices of healthy fresh fruit and vegetables. Following this overall trend, some of the studies included in the present review pointed to the stronger role of convenience stores relative to other food outlets (Howard et al., 2011). Wall et al. (2012) after analyzing different type of food outlets within 1 mile of adolescents' residences, found a significant effect of convenience and fast-food outlets on BMI for girls only. Harris and colleagues found convenience stores to be popular outlets where students obtain sodas (Harris et al., 2011). Galvez et al. (2010), using census blocks, and Leung et al., (2011), who used network buffers, found convenience stores to be significantly associated to BMI and BMI change respectively.

Many studies find the expected and significant relationship between BMI or diet and the presence of supermarkets or grocery stores (negative) or distance (positive) (Bodor, Rice, Farley, Swalm, & Rose, 2010; Cerin et al., 2011; Epstein et al., 2012; Moore, Diez Roux, Nettleton, & Jacobs, 2008; Rosenshein & Waters, 2009; Rossen, Curriero, Cooley-Strickland, & Pollack, 2013; Zhang, Christoffel, Mason, & Liu, 2006). In a study in Australia, Thornton and Kavanagh (2012) showed that individuals living in areas with the highest number of healthy food stores had a lower likelihood of purchasing fast-foods, albeit infrequently. Similar trends were found for children's BMI and food intake (Jennings et al., 2011). Interestingly, a study of supermarkets and fast-food outlets in Canada found that while the number of supermarkets and grocery store has declined, the number of fast-food outlets has grown over time (Smoyer-Tomic et al., 2008). Also worth noting is the evidence presented by Chaix et al. (2012) of the small share of individuals – around 11 percent- included in their analysis that shop in a supermarket located in their residential neighbourhood. Bodor et al. (2008), using linear shelf space for fruit and vegetable, along with availability of supermarkets and small stores, found that for the case of fruit and vegetable intake, each additional metre of shelf space led to a 0.35 serving per day increase.

Other studies fail to provide empirical support for the positive contribution of supermarkets to healthy outcomes. For instance, Hurvitz, et al. (2012) found that exposure to supermarkets varies little between home and away from home location. Hulst et al. (2012) found no association between children's intake and supermarkets, while access to fast-food and convenience stores was related to lower chances of eating or snacking out of home. Furthermore, Rose et al. (2009), using cumulative linear shelf space of fruits, vegetables and snack food within several network based geographic containers, found no association with BMI, except a weak and positive result for energy dense snacks. In another study by Hutchinston et al.

(2012) which used not only densities for different food outlets but also healthy foods linear shelf space , the researchers found the latter, and not the former, to be significantly negatively associated to adult overweight.Finally, Fietchner et al. (2013) found the opposite effect of supermarkets on BMI for a sample of children in Massachusetts, with a higher BMI for those living less than a mile from large supermarkets relative to those living more than 2 miles away.

2.2.5. Empirical Evidence -Gaps in the Literature

The studies included in this review provide important methodological and empirical contributions to the food environment literature and, overall, present evidence suggesting that food outlets, particularly supermarkets, convenience stores, and fast-food restaurants do play a role in dietary and health outcomes.

Still, despite the breadth of settings, populations, food measures and containers covered in these studies, several shortcoming can be identified that may have an impact in the study results and the comparison that can be drawn across studies, and underscore the importance of the present study. First, and as it was noted previously, the majority of the studies included one type of geographic container, and still a sizable number of them restricted their analysis to just one or two container sizes, precluding assessment of whether results are independent of the neighbourhood definition employed (Harris et al., 2011).

Some studies also limited their analysis to residential based containers leaving aside other areas that also comprise an individual's local food environment. Moreover, most studies assume that individuals in the same context have the same food environment, i.e. children within schools, without consideration of their actual activity spaces (Davis & Carpenter, 2009). Also, the use of different datasets to derive the food environment and health outcomes may introduce errors in the analysis, as outcome and food environment measures do not refer to the same subject (Kestens, Lebel, Chaix, Clary, Daniel, Pampalon, Theriault, & P Subramanian, 2012).

The few studies which have adopted ego-centric approaches have only used small sample sizes, restricting the analysis to a single spatial unit, a single day or a single season, which can compromise how the representativeness of the activity space (Christian, 2012b; Kestens &

Daniel, 2010; Kestens, Lebel, Daniel, Thériault, & Pampalon, 2010b; Zenk et al., 2011). Since the focus of the present study is the local food environment and children, it should be noted that most studies using an ego-centric approach focused mostly on adults. Finally, two issues that might compromise the robustness of results included in this review are the use of self-reported weight, and the approximation of residential address to the self-reported postal code centroid (Hutchinson et al., 2012). Previous studies on the topic have shown that using postal code centroids as proxies for actual addresses can lead to positional errors of up to 109 m on average in urban settings and even larger in rural settings from true locations (Healy & Gilliland, 2012). Furthermore, studies looking at perceived vs. measured weight have also found the first to depart from objective weight measurements, with variations by age, ethnicity (Beck et al., 2012; Brener, Eaton, Lowry, & McManus, 2004; Johnson, Bouchard, Newton, Ryan, & Katzmarzyk, 2009; Nyholm et al., 2007). It is therefore recommended that future studies take into consideration all of the aforementioned factors if they are to more accurately identify the link between local food environments and diet-related issues such as food purchasing, (un)healthy food consumption, and obesity/overweight.

Chapter Three: Conceptual Framework

3.1. What is the Role of the Environment on Individual Outcomes?

A growing body of research has identified the environment as a central factor behind many health-related issues, from how healthy people eat, to how much they exercise, how often they come in contact with open spaces, how much noise or pollution they encounter, how likely they are to access and seek health services, and in turn, how each of these issues ultimately impact individual outcomes.

Over the past few decades different disciplines have contributed to the place-based health literature by looking at whether place matters. This interest is underscored by a theoretical shift towards an ecological approach to health, which recognizes that geographic variation in health outcomes goes above and beyond the contribution of individual level characteristics (Kwan, 2012). In such ecological frameworks, health-related processes are affected by factors from multiple levels (i.e. individual, family, environment, political and social) (Kent & Thompson, 2012).

Empirical results from studies on environmental effects in epidemiology, contextual or neighbourhood effects in sociology, or spatial effects in geography summarized in various reviews present substantial evidence about the significance of place for people's health.

3.1.1. From Place Effects to Individual Exposure

While the question of an overall place effect has been addressed in the literature, the question of how or why place matters is yet to be resolved. We still lack coherent and robust empirical evidence of specific pathways between health outcomes such as obesity and environmental factors (Cummins et al., 2007)(Cummins et al., 2007; Dunn & Cummins, 2007).

As a result, there is a current discussion taking place in the literature about the fit of theoretical and conceptual developments used to demonstrate place effects. Similarly, methodological approaches that were central to understanding whether place has an overall unique contribution to health beyond that of individual characteristics are being called into question.

As noted by Spielman et al. (2009), our understanding of the environmental dynamics of health is directly related to the way we define and measure the construct of neighbourhood or local environment. Everything we can infer about contextual influences on health rest on, and is affected by, what we define as neighbourhood. Hence neighbourhood has been recognized as both a conceptual and methodological challenge in health studies, to the point of being dubbed as the “holy grail” of urban analysis (Spielman & Yoo, 2009) (Diez Roux & Mair, 2010; Spielman & Yoo, 2009).

The relevance of the notion of neighbourhood therefore lies not on how well we can define its boundaries, but rather on how well such boundaries represent people’s effective or natural space. In other words, neighbourhood is a useful conceptual or methodological construct insofar as it represents the right scale at which the impact of neighbourhood features on health operates (Root, 2012).

For instance, fixed administrative boundaries, such as census blocks or census tracts, have been popular for studying neighbourhood effects on health outcomes across racial, ethnic and socio-economic groups. They have also been key in studying neighbourhood differences in health outcomes (i.e. Cancer, Obesity, cardiovascular diseases) or health behaviours (i.e. smoking, drug and alcohol use) that can inform health policies or health promotion initiatives (Bernard et al., 2007; Dunn & Cummins, 2007).

Nevertheless, researchers have now revised the fit of such measures for analyses interested not on group-level processes, or neighbourhood level resources, but on the more nuanced issue of individual environmental exposure, which is affected by the spatial extent and mobility of individuals. Indeed, differences across individual daily activities that can be, and often are, located outside of the residential neighbourhoods translate into heterogeneous areas of environmental exposure (Perchoux et al., 2013). For the case of children’s activities, they are more likely to be bound to their home environment given their extrinsic mobility constraints, but it seems reasonable to assume that the actual spatial extent and shape of their local environment might not easily follow that of a pre-defined geographic area as arbitrarily bounded as a census tract (Rainham et al., 2010).

Cummins et al. (2007) proposed a relational approach to place that can yield better measures of exposure and advance our understanding of which environmental factors matter most for specific outcomes and individuals. This relational approach sees place beyond a Euclidean lens, varying over time and space, not tied to universal boundaries and used by mobile individuals. In addition, this approach dissolves the inadequate distinction between contextual – place-level and compositional – and individual level-effects that could explain the small and often weakly significant results in multilevel models, where each level is treated as independent from the other.

Rainham and colleagues also addressed both the relevance of place to health research and the problems that can arise when there is a misclassification of context and health outcomes, and point to the value of identifying both the pattern of individual movement over their local space and the variation of contextual characteristics across individual patterns (Rainham et al., 2010).

Kwan distinguishes between the most common "MAUP", or Modifiable Areal Unit Problems and what she defines as "UGCoP", or Uncertain Geographic Context Problems. The MAUP denotes the problem and effect of different aggregation levels of the same data – the *scale* component of MAUP – and different grouping of the same areal units – the *zonal* component of MAUP -- that can yield biased or invalid results (Kwan, 2012; Openshaw, 1984; Spielman & Yoo, 2009). While MAUP has received extensive attention in the literature, Kwan notes that less thought has been given to the UGCoP, denoting the imprecision of geographic contexts used in analysis, relative to the true geographic context of individuals where health outcomes are indeed affected by environmental features (Kwan, 2012).

Spielman and Yoo (2009) present evidence via simulation models about the under or over estimation of results if the choice of neighbourhood does not accurately represents the individual. As they appropriately point out, the problem does not lie on the use of neighbourhood zones, areas or frame, nor is adjusting the size or shape of said neighbourhoods a sufficient solution. Rather, the emphasis should be on deriving environmental influence measures from spatial extents reflecting the true neighbourhood.

3.2. How to Define Children's Food Environment

The built environment is defined as the physical environment that has been created by people, and includes infrastructure, buildings and open spaces (Bernard et al., 2007). To date, the built environment with respect to food has been characterized and defined using individual self-reported perceptions, or objective indirect and direct information about the types of food places they can access and the boundaries defining their local neighbourhood. The food environment can therefore be defined as the subset of the built environment related to the availability of food outlets, along with the quality, quantity and price of the food they offer and the advertisement of both outlets and food products.

3.2.1. Indirect Definitions

Indirect objective definitions of the built environment, also referred in the literature as territorial neighbourhoods, are based on a residential approach to local neighbourhoods, which are generally mutually exclusive, pre-existing geographic areas defined usually for administrative purposes, such as school catchment areas, census tracts or postal codes (Chaix et al., 2009). There is evidence, however, that such areas rarely correspond to 'natural neighbourhoods', and introduce 'edge effect' problems whereby those living in the limits of the administrative unit might be incorrectly represented by the spatial unit of choice (Sadler et al., 2011). For instance, use of centroids from reported polygon areal data such as postal codes or census tracts can also introduce error depending on how misaligned they are with the actual individual residential coordinates (Healy & Gilliland, 2012; Thornton et al., 2012b). Similarly, Sadler et al. (2011) presented evidence of edge effects leading to over-reporting of distances to food outlets.

3.2.2. Direct Definitions

On the other hand, direct definitions of the neighbourhood environment center around individual's home and are associated with the epidemiological tradition seeking to define local exposure areas (Chaix et al., 2009). This approach to neighbourhood is derived from either subjective (i.e., self-reported, perceived) data or objective data. Although inaccessibility or higher costs might prevent many studies from using objective data, it is preferred since it overcomes issues of reporting bias whereby participants might prefer to omit areas they do not feel are, or want to consider as, part of their local neighbourhood despite being effectively exposed to them. In addition, research has shown that perception of neighbourhoods might differ by individual outcomes such length of residence, education or income and neighbourhood characteristics such as census tract density or land use (Coulton et al., 2013). Direct definitions of the neighbourhood can be further classified as residentially-based and ego-centric based definitions.

3.2.2.1. Residentially-based Neighbourhood

Individual or ego-centred places have as starting point the individual location, usually the home address, and extend outward a pre-defined distance, but need not have mutually exclusive boundaries (Perchoux et al., 2013). Local environments are derived either through Euclidean or street network buffers. Circular buffers have been amply used in the literature, are easy to derive, and allow ease of comparison across context given their standard size and shape. However, they also bring other limitations, particularly in areas where barriers such as rivers, railways, bridges or lakes may render portions of the buffer outside of the natural environment of individuals.

Road network based residential buffers have been used as an alternative that better reflects the local environment accessible to people. The literature generally rates network buffers as more accurately describing distances individuals might travel to destinations, given that they are likely following the street network and are thus, a better representation of the local neighbourhood experienced by a person as they walk through it. However, this too can prove susceptible to error in areas with low street network density or irregular patterns that might render larger local environment or neighbourhoods than those actually used by individuals. In addition, these statements do not necessarily apply to children, who might use shortcuts when moving around their environment and are more likely to travel through parks and sometimes public buildings than along sidewalks or roads.

There is no agreement on which distance best represents the local environment around an individual. This is particularly challenging when considering the built environment around children, with even fewer studies providing grounds for comparison between different distance thresholds. Ball (2006) points out that the distance criteria to define children's neighbourhood relates to aspects such as children's mobility, children's or parents' activities in or outside the neighbourhood, and call for research that investigates the effect of different sized-buffer zones for environmental exposures.

Surprisingly, only a small number of studies have focused on determining whether measures of the food environment are significantly different according to choice of scale or geographic boundary or container.

3.2.2.2. Ego-centric based studies

Activity Spaces

The concept of activity space is not new, with early references linked to the time-space approach by Swedish geographer Hägerstrand (1970). The notion of activity spaces refers to the area within which individuals move or travel (Long et al., 2012). They might represent the space continuously utilized by an individual, or the set of locations visited by an individual within a specific window of time (Thornton et al., 2011). In that sense, activity spaces allow a conceptualization of local environment as individually experienced, rooted in time and place and based on a mobile individual. They are structured around the home domain, but are flexible enough to include the locations around which an individual moves and the journeys between them (Perchoux et al., 2013). Research on the activity spaces of children can also be traced back to several decades ago (Andrews, 1973), although the number of studies have been on the rise only recently.

Activity spaces can be a fitting abstraction of the spatial behaviour of an individual, corresponding to the areas of their residential, school or work environment they frequent most often. Thus, it is reasonable to assimilate activity spaces as an accurate measure of a local environment and its corresponding environmental hazards or amenities (Mennis et al., 2013). In addition, the application of activity spaces in environmental psychology is particularly relevant to research on children. Perchoux (2013) describes the emphasis this discipline puts on place identity and perception. Place attachment shapes individual's use of activity spaces, making, for instance, some locations and features more salient, and, at the same time, the frequency of interaction with such places underscores the establishment of these emotional ties.

A great deal of attention has been paid to the measurement of activity spaces that are derived from discrete locations through surveys and diaries. The most notorious approaches in the literature are standard deviational ellipses, found useful to describe and analyze the dispersion of activity spaces, and minimum convex polygon enclosing all the destination places within a given timeframe (Buliung & Kanaroglou, 2006; Vallée et al., 2010) (Buliung & Kanaroglou, 2006). Standard deviational ellipses (DEs) are one of various centrographic methods to describe spatial properties of point patterns, and can be found in the literature as early as the 1920s (Buliung & Kanaroglou, 2004). They are typically based on the mean center of all points of activity (typically measured by GPS points), and the shape of the ellipses characterizes the spatial attributes – location, dispersion and orientation – of the activity space of each subject.

Home Range

A similar concept that is making its way into studies of health and place is the 'home range', which has most often been applied by ecologists, in their studies of animal movement data (Long et al., 2012). The notion of home range seeks to represent the spatial area where the typical daily activities of an individual take place. In the ecology literature, home ranges are usually measured as the minimum enclosing polygon area where the majority of the individual's movement are included. Within this home range, a core area can be distinguished, denoting the space where activity is concentrated, typically defined as including 50 percent of the individual's movement and akin to the notion of home environment (Downs et al., 2011). Home range and core area are therefore informative concepts that describe not only the use of space without a priori limitation as to what that space might look like, but they also rules out locations that are infrequent or arising from data collection imprecision or data processing errors. Over the past decade, some studies have taken advantage of GPS technology to apply the concept of home range to study the effect of place on individual activity (Rainham et al., 2010).

3.2.3. Concluding Remarks

Ego-centric definitions of local neighbourhoods constitute a step forward for research on the role of the built environment and individual outcomes. They are a relevant and accurate approach that considers the use of space for a specific person that is not restricted by residential boundaries. For children, too, activity spaces are an improvement over traditional pre-defined geographic definitions. Activity spaces include only the places intersecting the area where children are more likely to move, and as such are places that are either used, perceived or at the very least are potentially accessible to them. In other words, the activity space derived from travel or activity diaries, GPS tracks, or surveys constitute only a snapshot of the local environment used, explored, and perceived by children. Thus, activity spaces are an important indicator of the potential and realized influence of the built environment – or the food environment for the present study – on children's behaviours and actions.

As Matthews points out, adults' and children's lives unfold in a "continuous and anisotropic world", where more often than not journeys and movement cluster around nodes or domains such as the neighbourhood, home, school or work. Moreover, the temporal and spatial scale of local environments varies between individuals, with likely patterns emerging between those living in similar contexts (Matthews, 2012). Kestens et al. (2012) agree with this call for exposure measures that reflect the "spatial polygamy" of daily life and provide empirical support for the improvement of food environment measures based on activity spaces. In addition, Villanueva et al. (2012) note that variation in children's activity spaces is significantly related to such things as parental perception of traffic, independence, or local destinations, which again, implies that traditional neighbourhood boundaries do not necessarily reflect children's local environment.

Only recent developments in data acquisition, such as the use of GPS for health research and data analysis, particularly in geographic information systems, and the corresponding computer processing requirements, have allowed researchers to use the concept of activity space in studies of the built environment. Only a handful of studies have assessed the influence of the food environment on individual outcomes via activity spaces, where the local environment is not bounded to one anchor point such as home, school or work, but rather is constructed on the basis of all places where daily activity unfolds.

Finally, it should be emphasized that GPS is a critical tool for data collection on the movement in and use of children's local environments, as it overcomes issues of self-reporting errors, inaccurate locational and time data, and participant burden that are even more likely to occur in studies of children. GPS tracks overcome the arbitrary pre-defined geographic units such as census tracts or postal codes, as they allow the researcher to construct activity spaces that are based on their subject’s actual movements, and therefore can yield local environments that reflect with more precision in defining children’s true local environments. (Ohmori et al., 2000)

Chapter Four: Methods

3.3. Data Sources

3.3.1. STEAM Project and Sample

Data for this study were derived from the “Spatio-Temporal Environment and Activity Monitoring” (STEAM) project housed at the Human Environments Analysis Laboratory (HEAL) in the department of Geography, at Western University in London, Ontario, Canada. The project is being led by Dr. Jason Gilliland and is jointly funded by the Heart and Stroke Foundation of Canada and the Canadian Institutes of Health Research. The STEAM project is a multi-year, multi-method protocol involving the collection of objective GIS data on local built environments, objective physical activity data (collected with accelerometers), objective spatial activity data (collected with portable GPS), and qualitative data on children's preferences and perceptions through the use of validated survey and diary instruments. The sample population in this study includes children aged 11-14 years of age attending a heterogeneous sample (by income and built environment) of elementary schools throughout the city of London, Ontario. Ethics approval was obtained through the Office of Research Ethics at Western University and the four participating school boards. In addition, informed written consent was obtained from parents and written assent was obtained from students prior to the start of the data collection. The preliminary sample used for this thesis includes 492 children.

GPS data collected for each participant in the STEAM, was used to construct the geographic containers in this study, after it was cleaned and processed following a GPS protocol develop by the HEAL. Children were instructed and trained on how to wear a Visiontac GPS receiver over seven days in and out of school. The GPS units chosen for the project have high precision (up to 1.5m accuracy with DGPS support), a short time until first fix (i.e., approx. 1 second hot), a battery life that lasts up to 24 hours while logging tracks, and recording capacity of up to 25 million waypoints; furthermore, their small size, weight and ease of use make them appropriate for children's use. Data collection took place over four weekdays and one weekend for each school in the study, with two or three schools scheduled in the same week. The schedule took place over a period of 6 weeks during the spring semester to minimize the effect of weather on children's activities. In addition, daily field work included qualitative weather logs recorded by project team members. Field data collection was schedule on weeks with no holidays, field trips or other special activities that could lead to a departure of a regular school day.

Members of the research team meet with the students every day of the project to download the data, log children's feedback about their GPS units and inspect and replace them when needed. Once field work is completed, all raw GPS data files corresponding to each participant are combined, cleaned and processed using a C^{++} program developed by the HEAL to convert the GPS points into decimal degrees, calculate time blocks to use in analysis, and according to the appropriate school schedules, calculate and add a confidence value, add ID and time fields and headings, and import into a geodatabase in ArcGIS.

Student home locations were obtained by calculating spatial means of all their GPS points in and around the child's home. Finally, a home walk extent for each student was produced using geoprocessing tasks automated through model builder in ArcGIS 10.1. GPS points for each participant were filtered to exclude points corresponding to the time blocks within school, points that have an associated speed of more than 22 kilometers per hour, or with an associated bus or car mode of travel.

3.3.2. Geographic Containers

The analysis presented in this study utilizes direct activity data to derive two types of residentially based and two types of ego-centric based geographic containers to define the local food environment around children. All the geographic containers are based on GPS tracks collected over a period of four weekdays and 2 weekend days to maximize representation of children's local environment during and outside of school days. All the containers used in the analysis overcome the problems associated with administrative boundaries that impose arbitrary limits on the definition of local food environment as has been mention in the previous chapter. All analyses were conducted using ESRI's® ArcGIS® version 10.1 (Environmental Systems Research Institute, Inc., Redlands, California).

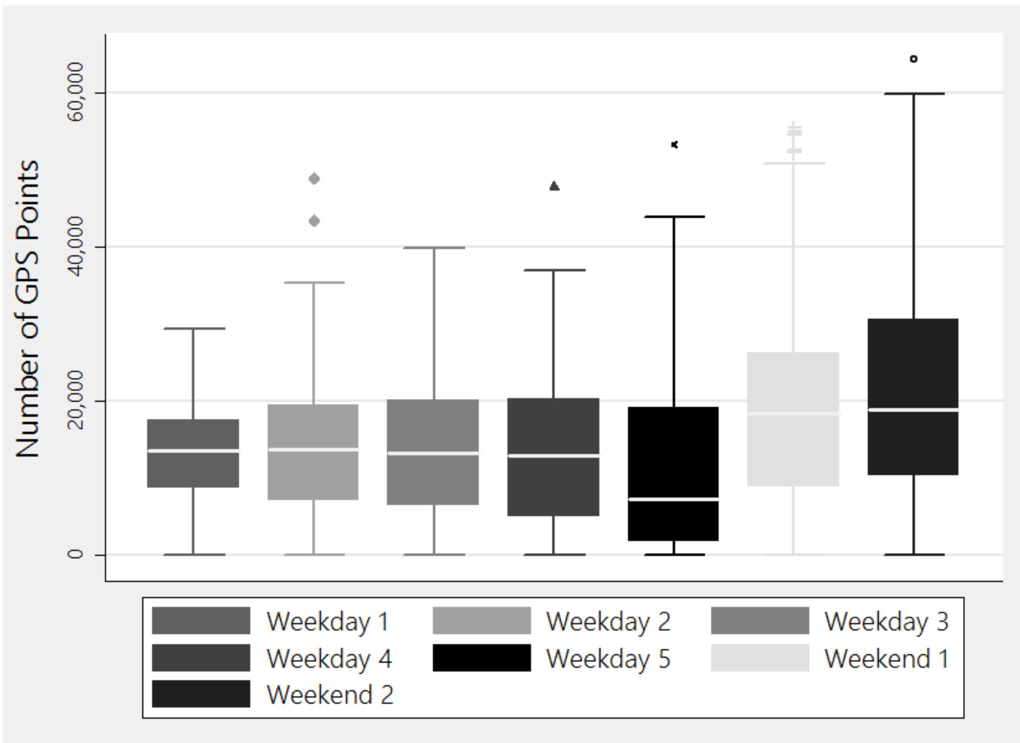

Figure 4. STEAM project – Box Plot of Number of GPS Points across Participants

Figure 4 shows the distribution of GPS wearing time across participating students. Students without at least one complete GPS route were excluded from the analysis (n=18), since their residence point and activity spaces could not be accurately obtained. The analysis included 13 different polygons for each of the 474 children in the final sample, for a total of 6162 geographic containers.

3.3.2.1. Euclidean and network buffers

Euclidean and network buffer containers were obtained for each student in our sample using model builder geo-processing routines in ArcGIS 10.1. Following school board criteria for school bus eligibility, buffer containers for four different distances were included, 400 m, 800 m, 1200 m, and 1600m, and are assumed to be likely walkable distances for school-aged children.

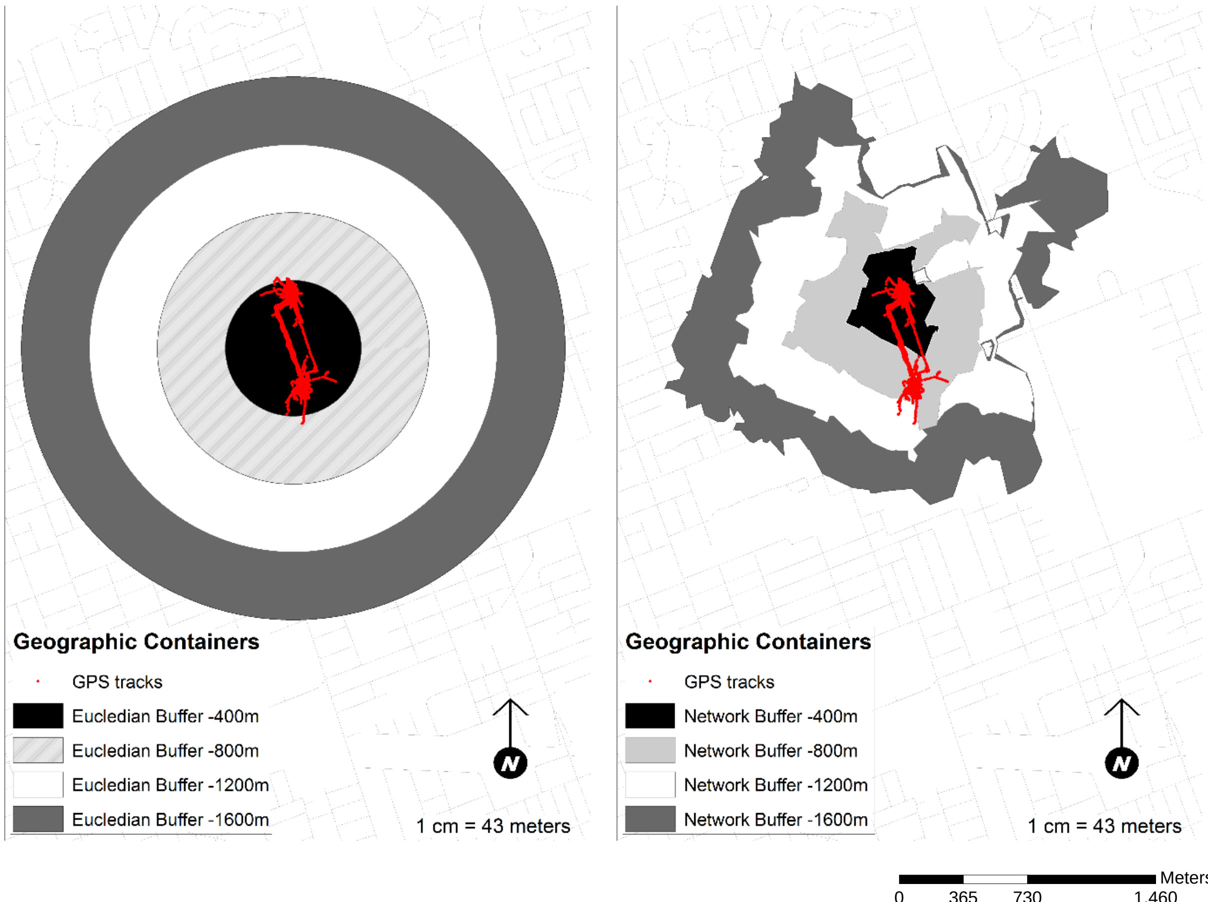

Figure 5. STEAM project –Example of Euclidean Buffers (Left) and Network Buffers (Right)

The circular buffers include the local neighbourhood around children's residence for each of the distance bands "as the crow flies" (i.e., Euclidean distance). Network buffers also include the local neighbourhood around children’s residence as defined by distances along the street network, and were derived using the “service area” tool available in the Network Analyst extension in ArcGIS10.1 for each of the four distance bands. Figure 5 shows an example of the

Euclidean and network buffers for the same child with the corresponding GPS points overlaid in red.

3.3.2.2. Activity Space- Standard Deviational Ellipses

One of the ego-centric definitions used in the present studies are standard deviational ellipses (SDE) obtained using ArcGIS 10.1 Spatial Statistics extension. As was described in the previous chapter, SDEs are visual descriptions of the distribution of a child's GPS track points along a longitude and latitude dimension and have been one of the standard methods to derive activity spaces (Buliung & Kanaroglou, 2006; Vallée et al., 2010).

Figure 6. STEAM project –Example of Activity Space SDE Ellipses

For each participant, one standard deviation ellipse that includes 68 percent of the GPS points and two standard deviation ellipses that include 95 percent of the GPS points were obtained (See Figure 6).

Both SDE geographic containers use only the GPS points corresponding to each student's walk extent, described in this section. This restricts the analysis to only those points that reflect children's local environments, excluding GPS tracks corresponding to times and areas of commuting by motorized vehicles. The resulting activity space containers are, thus, effectively capturing the extent of the local food environment around children's two main domains: school and home. SDEs are a way of summarizing the size and orientation of the minimum ellipsoid area enclosing all the activity pattern locations captured across the six fieldwork days.

3.3.2.3. Activity Space- Concave Hulls

The analysis also includes another ego-centric activity space container that is based on α-hulls. The α-hull is a generalization of the convex hull, which is the minimum enclosing convex polygon for a set of points in space. They have been found to yield more refined home range areas in ecology studies (i.e., activity spaces for the set of GPS tracks for any given child in the present study) than either convex hulls or minimum bounding box polygons (Burgman & Fox, 2003). They yield a detailed description of the underlying points, and a more reliable shape for irregular point ranges, with the possibility of several discrete hulls for isolated group of points (Raedig et al., 2010).

The α-hulls[1] were generated using R software version v.2.16.0 (R Development Core Team, 2012), which imported child GPS shapefiles corresponding to their walk extents along with their projection parameters, derived an α-hull object for three different alpha parameters, and converted the α-hull object into a spatial object, and exported them back into an ArcGIS format.

[1] The script was written by the author and can be provided by request. The script uses the RGDAL, SP, MAPTOOLS, SPDEP RGEOS and A-HULL libraries along with a user-written script developed by Dr. Andrew Bevan - a.bevan@ucl.ac.uk- to convert the α-hull object into a spatial object -ah2sp.R-.

The alpha parameter defines how coarse or fine the resulting hull shape is, with larger alpha leading to a maximum coarse shape of a convex hull. The R function produces Delauney triangulation of all the GPS points for each child, with lines joining the points constrained so that no lines intersect between points, calculates the average distance length for all the lines between GPS points, keeps only the lines that are α times this average length, and derives the hull shape from all the remaining triangles (Raedig et al., 2010). For the present study, an α parameter of 10 was used for the finest shape, an α parameter of 30 was used for a mid-sized shape, and an α parameter of 100 was used for a more coarse activity space container (see example in Figure 7).

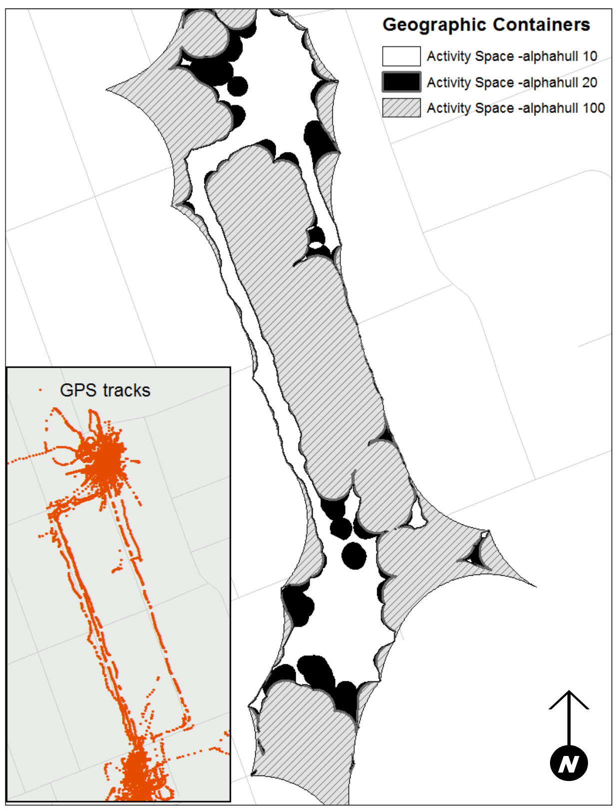

Figure 7. STEAM project – α-hull Activity Space and actual GPS tracks (inset)

3.3.3. Food Environment Measures

Using a comprehensive food establishment inventory dataset provided by the health inspectors of the Middlesex London Health Unit (2010) and verified by members of the HEAL, food outlet locations were geocoded to their exact location (i.e., centroid of building footprint). Building upon standard classifications included in the health inspector database, five categories of food outlets were defined as relevant for the present study: 1) fast-food or limited service outlets, 2) full service restaurants, 3) supermarkets or grocery stores, 4) fresh produce and farmer market outlets, and 5) convenience or corner store outlets. Supermarkets were defined by big regional or national chains, whereas small, locally-owned variety/grocery stores, or convenience stores attached to gas stations were categorized as convenience food outlets. To do so, food outlets were manually classified either by name recognition and local knowledge of the study area, or by information obtained through Google maps plus Google street view, or 'ground truthing' (i.e., site visits) to verify that the name and address were correct and that the outlet was still operating. The following types of food outlets were excluded given their low likelihood of accessibility and independent usage by children between 10 and 15 years: wholesale foods;liquor stores, bars and taverns; community kitchen and child food programs; food outlets located in private facilities such as hotels, hospitals or universities; mobile food outlets; food caterers and banquet facilities; and food processing facilities. The final 2010 database included relevant food out of 2637 food facilities.

Fast-food outlets were defined as restaurants where customers ordered at a counter and paid in advance for their food. This category includes franchised fast-food chains, carry-out food outlets, ice cream shops, pizza take-outs. The majority of convenience stores and grocery and supermarkets were correctly classified by the health inspector database and minimum changes were made, mostly related to change of name, and open status.

ArcGIS 10.1 was used in order to obtain measures of the food environment for each of the four outlet types, restaurant, supermarket, fast-food outlet, convenience stores, and number, along with a variable for the total number of unhealthy outlets for the set of STEAM project participants that lived within the boundaries of Middlesex county (N= 440). Using the iteration features in model builder, we carried out a spatial join between the food environment dataset and the geographic containers described below. For some of the containers, the number of the various food outlets was quite low, preventing the estimation of other commonly used approaches to food environment in the literature, namely, RFEI indexes. Instead, the number of each of the types of food outlets was derived for each child in the study, along with a combined variable capturing the total number of unhealthy food outlets: operationalized as the number of convenience stores and fast-food restaurants.

3.3.4. Statistical Analysis

Two objectives of the present study are to examine whether, and to what degree, geographic containers used in the literature to represent children's local environment accurately capture their actual use of space, and to assess the influence of the geographic container chosen on the food environment measures for each of the four common food outlet types included in the analysis.

With that in mind, two distinct analyses to be conducted are: a) an examination of the percent agreement of the geographic area between each of the geographic containers, and more importantly, b) a statistical test of the agreement and correlation of food environment measures between the different geographic containers.

To address the first analysis, and through model builder in ArcGIS 10.1, an iterative intersect function was used to obtain the percent overlap between the α-hull activity spaces and each of the traditional Euclidean and standard buffers. Given the α-hull activity space containers have been derived from actual GPS tracks over a period of a week, we can infer to what degree the traditional residential-based buffers provide accurate representations of children's local food environment.

Regarding the second analysis, and following Lian et al. (2012), Kappa statistics were used to evaluate the food outlet measure agreement between containers, or, in other words, how similar the measure for each type of food outlet is across the specific definition of local food environment. Kappa statistics are often used in studies looking at agreement between measurement methods related to GIS (Arbour & Martin Ginis, 2009; K. Ball et al., 2008; Jilcott, Evenson, Laraia, & Ammerman, 2007; Rozenstein & Karnieli, 2011). In essence, Kappa is based on the percentage of agreement between two maps, corrected for the fraction of agreement that can be expected by *pure chance*.

Kappa is defined by:

$$Kappa = \frac{P_{0-}P_C}{P_{p-}P_C}$$

With *Po* being the observed proportion correct, *PC* is the expected proportion correct due to chance, and *Pp* is the proportion correct when classification is perfect Pontius (2002).

Kappa values ranges between 0 and 1, with 0 indicating no agreement and 1 indicating perfect agreement with the value of kappa denoting the percent decrease in error versus a classification generated randomly. Kappa values are interpreted as follows: values smaller than 0.20 indicates less than chance agreement, between 0.01 and 0.20 slight agreement, between 0.21 and 0.40 fair agreement, between 0.41 and 0.60 moderate agreement, between 0.61 and 0.80 substantial agreement and between 0.81 and 0.99 almost perfect agreement (Viera & Garrett, 2005). The null hypothesis of the Kappa test states that two independent classifiers – geographic containers for the present study -- do not agree on the rating or classification of the same object, in this case the food outlets for each type of food outlet.

All analyses were conducted using STATA Version 10.1 (Stata-Corp, College Station, TX, USA). A P value <.05 was considered statistically significant.

Chapter Five: Results of the Geographic Container Methodological Comparison

Three α -hulls derived were overlaid for visualization for each child in the sample. The overlays consistently show no discernible pattern regarding the similarity or dissimilarity between the derived polygons. Furthermore, the degree of similarity seems to relate directly to the complexity of the pattern of GPS points. As can be seen in Figure 7- Figure 10 (inclusive), there are a wide variety of shapes across students and between α parameters. The α-hull with the smaller α parameter seems to yield a more accurate shape than the α =100 polygon, particularly for some students with larger activity spaces, as evidenced by the GPS tracks (in orange) presented in Figure 7. On the other hand, students with smaller activity spaces, for instance, spanning less than two blocks, yielded similar shape and sizes for all α hull parameters (See Figure 8).

Students with GPS tracks that showed a core area and a linear path, usually following the street network, resulted in shapes that were better described by a low alpha parameter (See Figure 9). For children with GPS tracks that took place in a single core area, polygons for the three parameters appear similar. However, the suitability of the activity space with α parameter of 10 cannot be generalized, as for various cases the α-hull function yielded better results from the α parameter of 100 (See Figure 11).

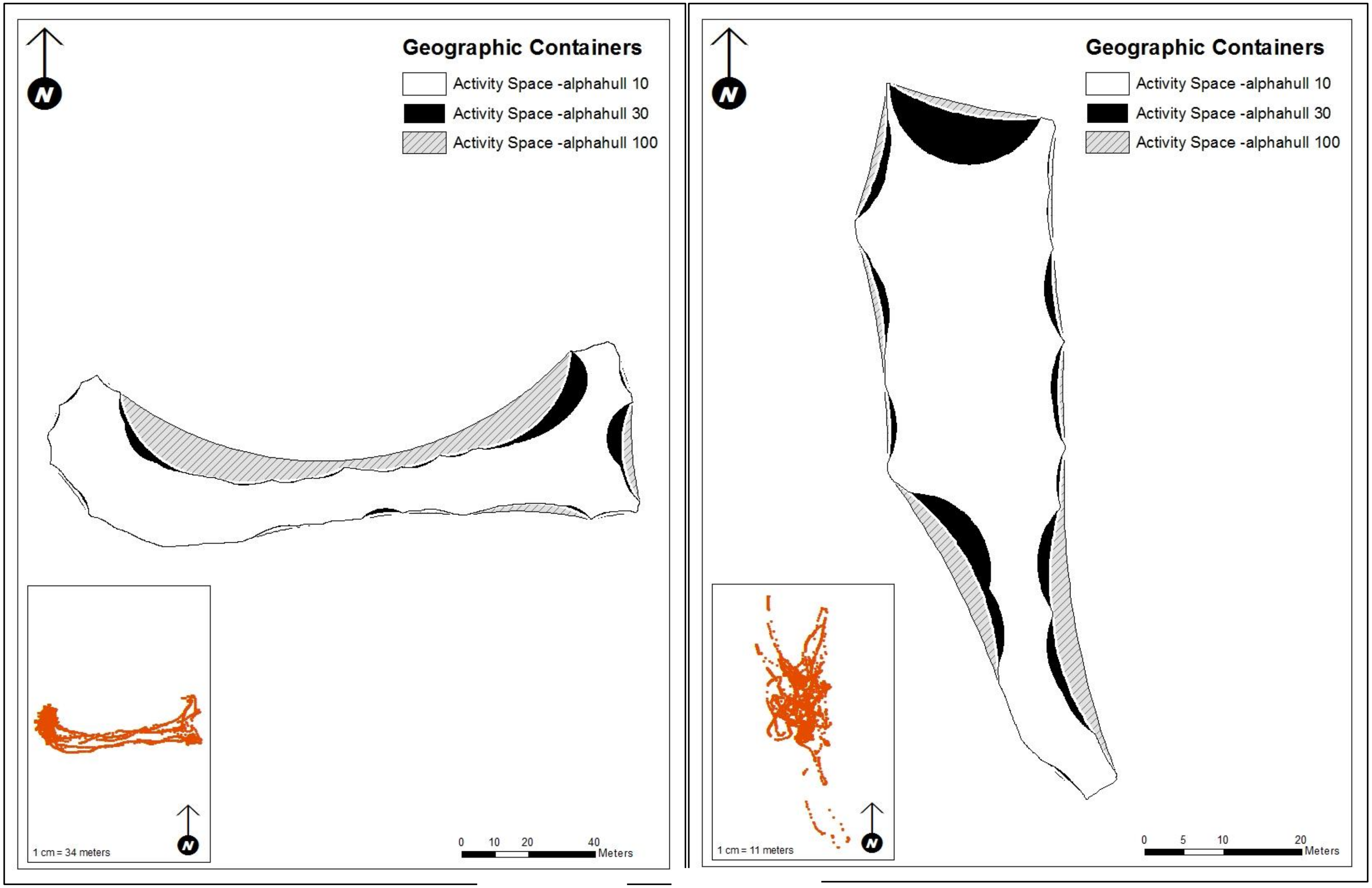

Figure 8. STEAM project – α -hull Activity Space and actual GPS tracks (insets)

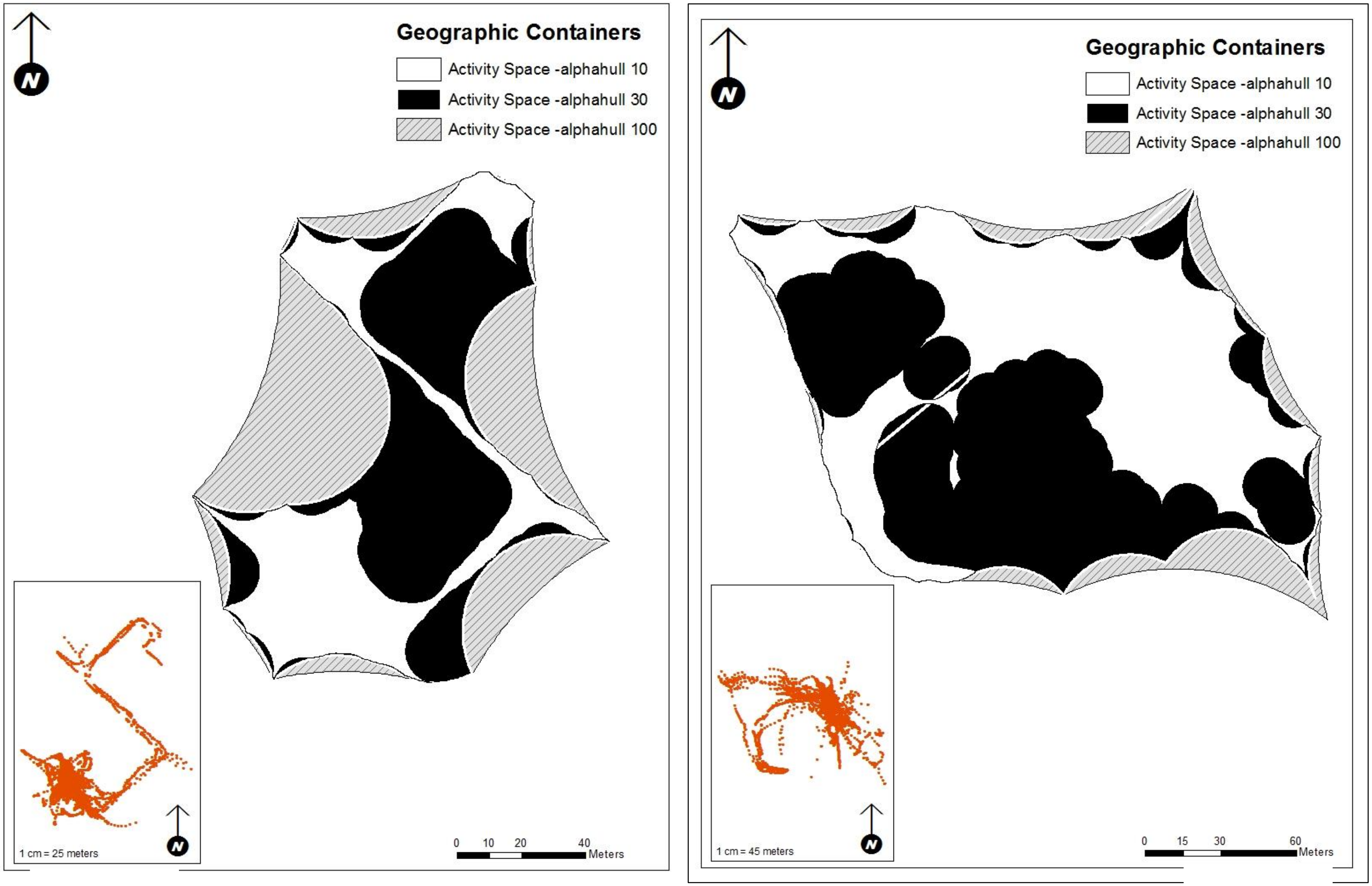

Figure 9. STEAM project – α -hull Activity Space and actual GPS tracks (insets)

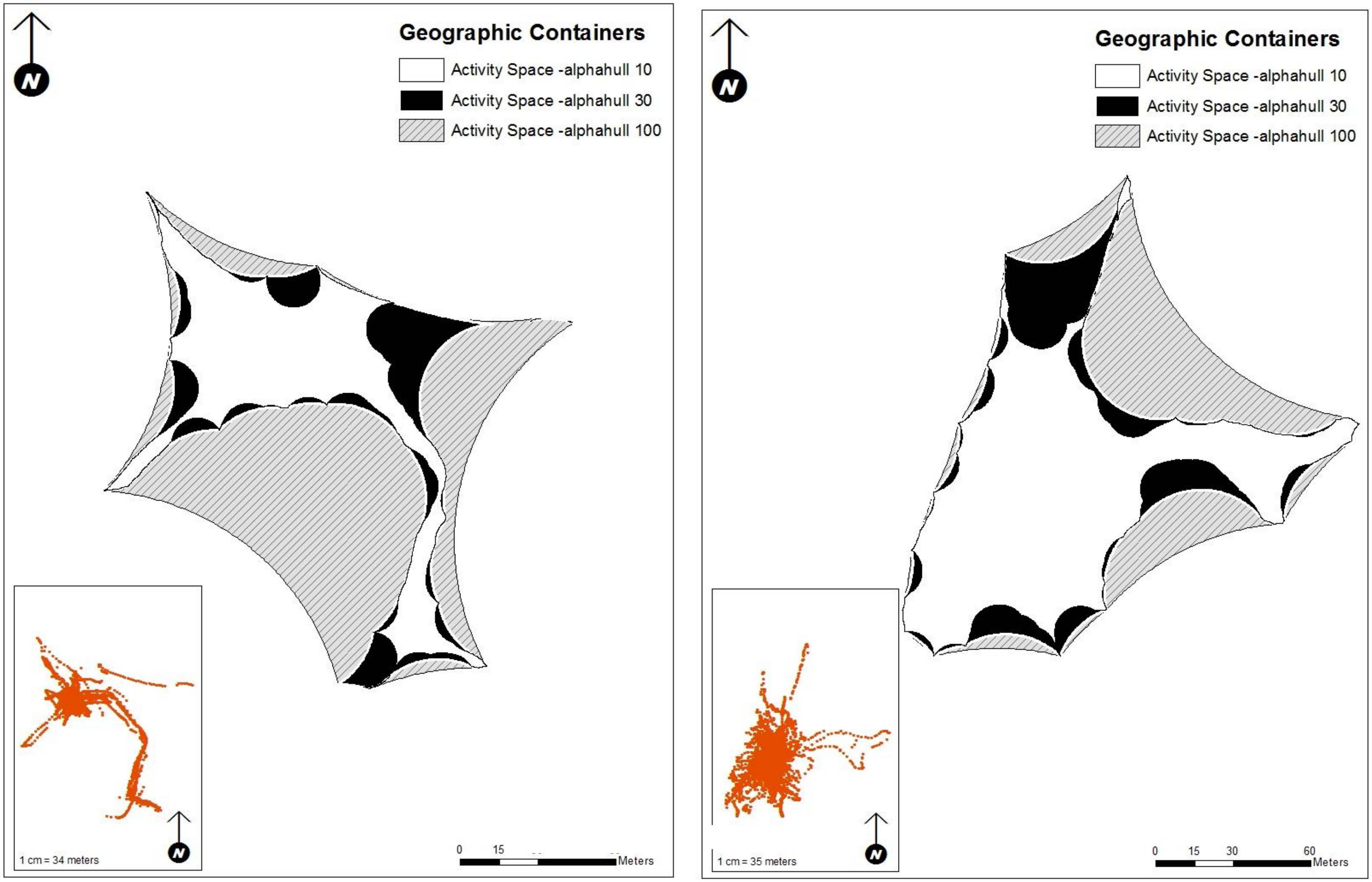

Figure 10. STEAM project – α -hull Activity Space and actual GPS tracks (insets)

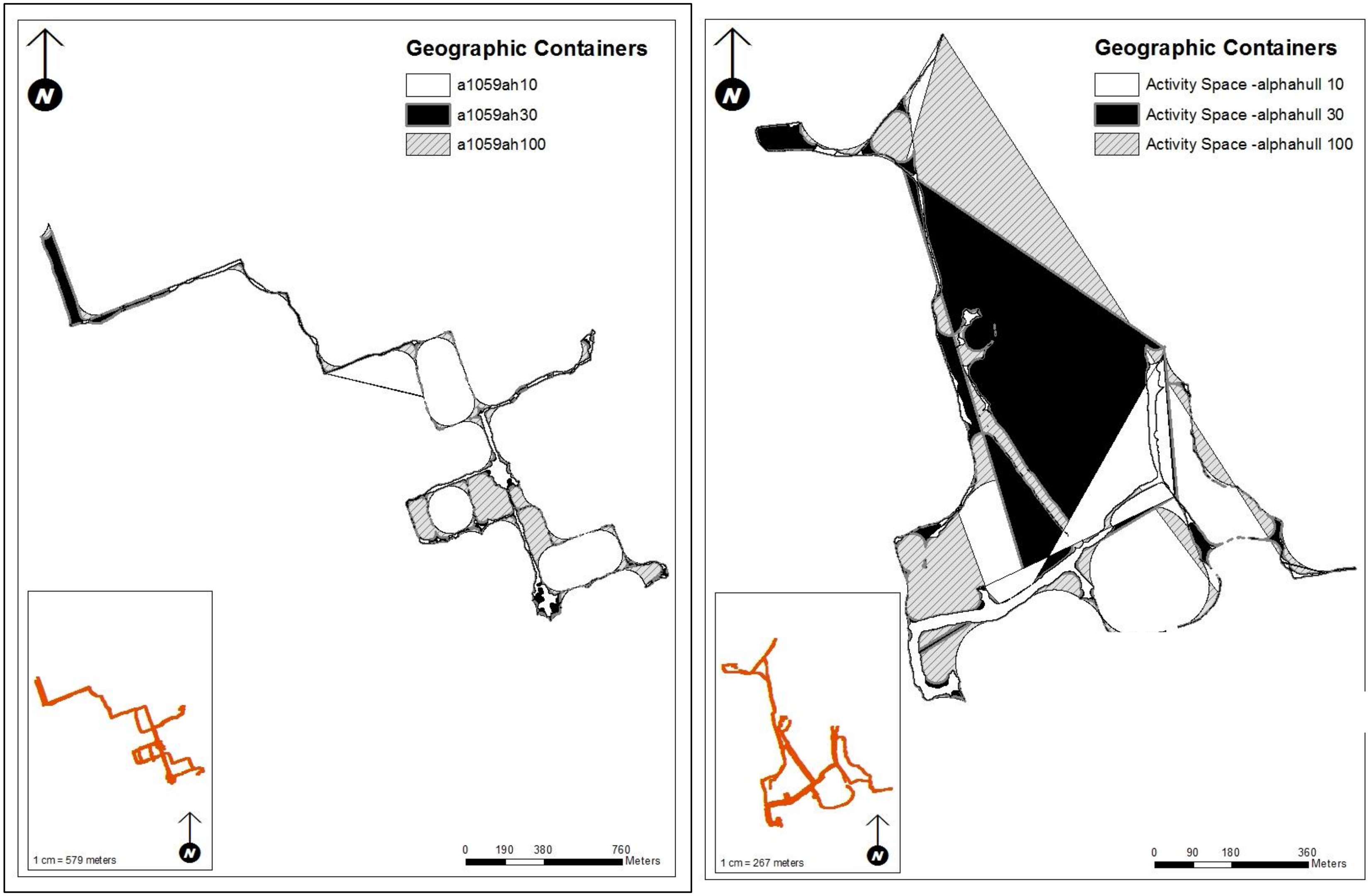

Figure 11. STEAM project – α -hull Activity Space and actual GPS tracks (insets)

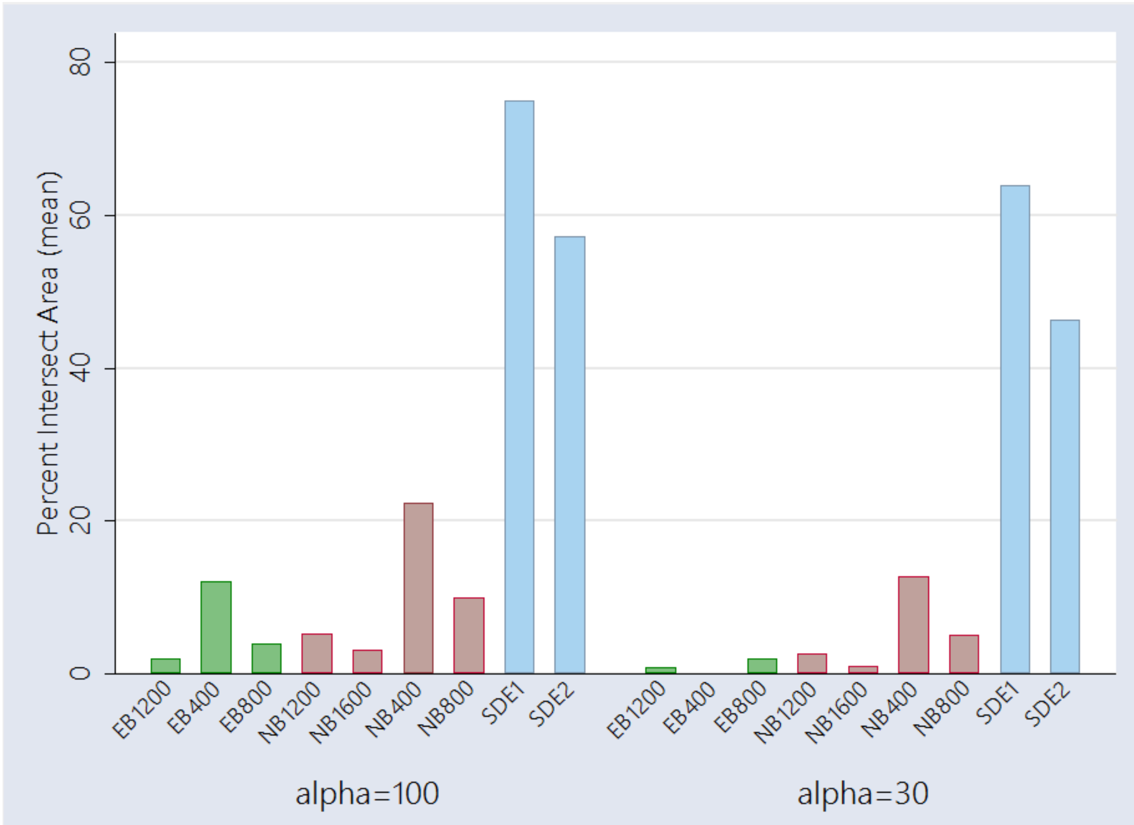

Figure 12. Percent Shared Area between α-hull and Geographic Containers
(NB= Network Buffer; EB= Eucledian Buffer; SDE1= 1 Standard deviational Ellipse; SDE2= 2 Standard Deviational Ellipses)

Figure 12 shows the percent overlap between α-hull- based activity space and the various geographic containers, Euclidean buffers, network buffers and standard deviational ellipses. For ease of visualization, the alpha-hull=10 has been omitted. As expected, the smaller network buffers have a larger shared area with all three activity spaces, particularly with the activity space α=100, which has the largest intersected area with all the traditional network buffers. However, overall alignment between the areas of alpha-hulls and the residentially-based containers (across all sizes) is considerably small, with a mean percent area intersected with the alpha-hulls no larger than 25 percent for the residentially-based containers. On the other hand, standard deviational ellipses have considerably higher alignment with the alpha-hulls, ranging from 45 to 75 percent of intersected areas. This is more evident with larger α-hull parameters and therefore coarser derived polygons.

Given that residentially-based network buffers are a major improvement over previously area-based containers such as postal codes and census tracts, it was anticipated that at least the smaller buffer would closely resemble the actual local environment used by the sampled children.

Table 1 presents detailed summary statistics for the percent of overlapping between the areas of the α-hull activity spaces and the residentially-based network buffers. It can be seen that α-hulls, on average, represented only between 0.50 and 22.04 percent of the network buffers. In addition, although a small number of intersected pairs shared more than 70 percent of their geographic extent, 75 percent of the activity spaces have at most 11 percent (α =10), 16.5 percent (α =30) or 31 percent (α =100) of shared geographic area with any of the buffers, while 95 percent have an overlapping area no larger than 58 percent.

Table 1. Summary Statistics for Percent Intersected Between α-hull Activity Space and Network Buffers

Buffer Size	Mean	S.D.	Min	Max	25%	50%	75%	95%
Activity Space -Hull α = 10								
400m	8.51	7.64	0.05	55.20	3.39	6.49	11.12	23.17
800m	3.39	3.87	0.02	38.21	1.05	2.30	4.42	9.62
1200m	1.72	2.16	0.00	23.07	0.48	1.08	2.13	5.25
1600m	0.50	0.56	0.00	2.33	0.23	0.32	0.50	2.17
Activity Space -Hull α = 30								
400m	12.56	10.04	0.07	70.29	5.40	10.43	16.44	31.63
800m	4.90	4.53	0.02	32.49	1.77	3.68	6.43	13.79
1200m	2.50	2.40	0.01	17.65	0.86	1.78	3.28	7.28
1600m	0.98	1.38	0.01	7.41	0.31	0.52	1.01	3.41
Activity Space -Hull α = 100								
400m	22.04	17.28	0.06	84.03	8.99	18.00	31.39	57.56
800m	9.77	9.50	0.02	63.87	2.97	6.81	14.20	26.17
1200m	5.06	5.27	0.01	32.15	1.34	3.39	7.24	16.34
1600m	2.96	3.32	0.01	18.45	0.65	1.74	3.98	10.25

Figure 13 through 17 (inclusive) present an overlay of 11 of the 13 buffers produced in the analysis (buffers with a distance of 1600 have been excluded for ease of visualization).

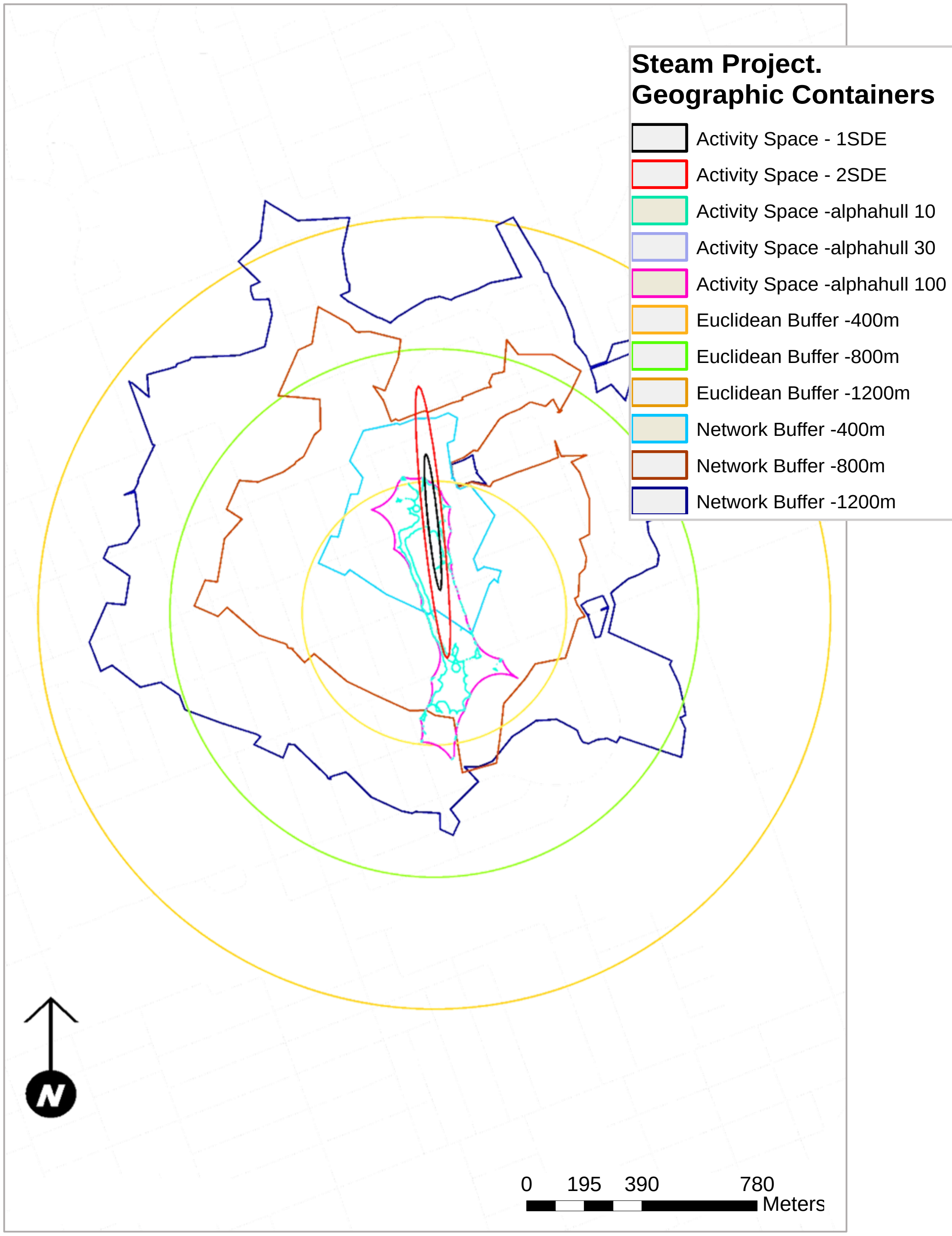

Figure 13. STEAM project – Overlay of the Geographic Containers

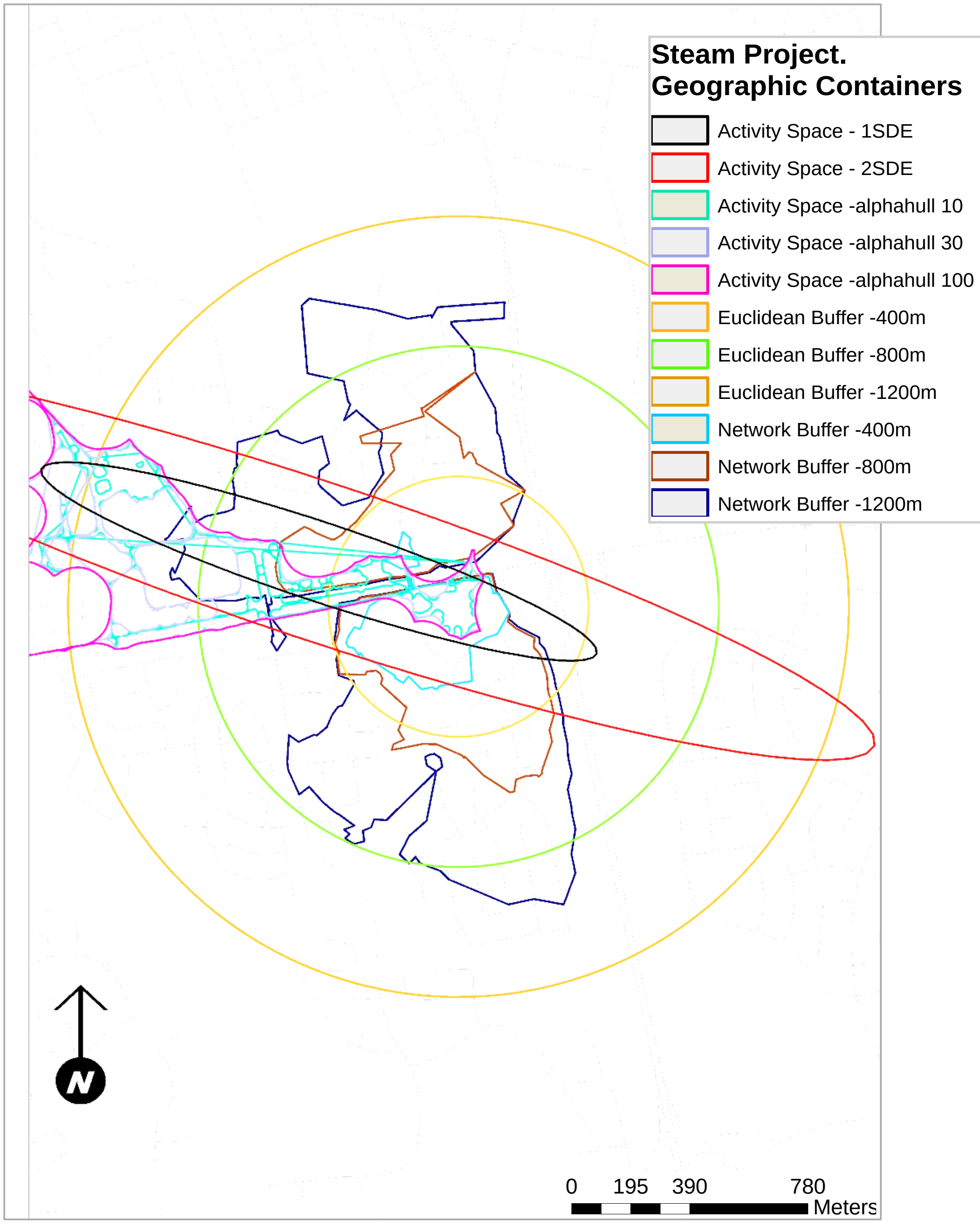

Figure 14. STEAM project – Overlay of the Geographic Containers

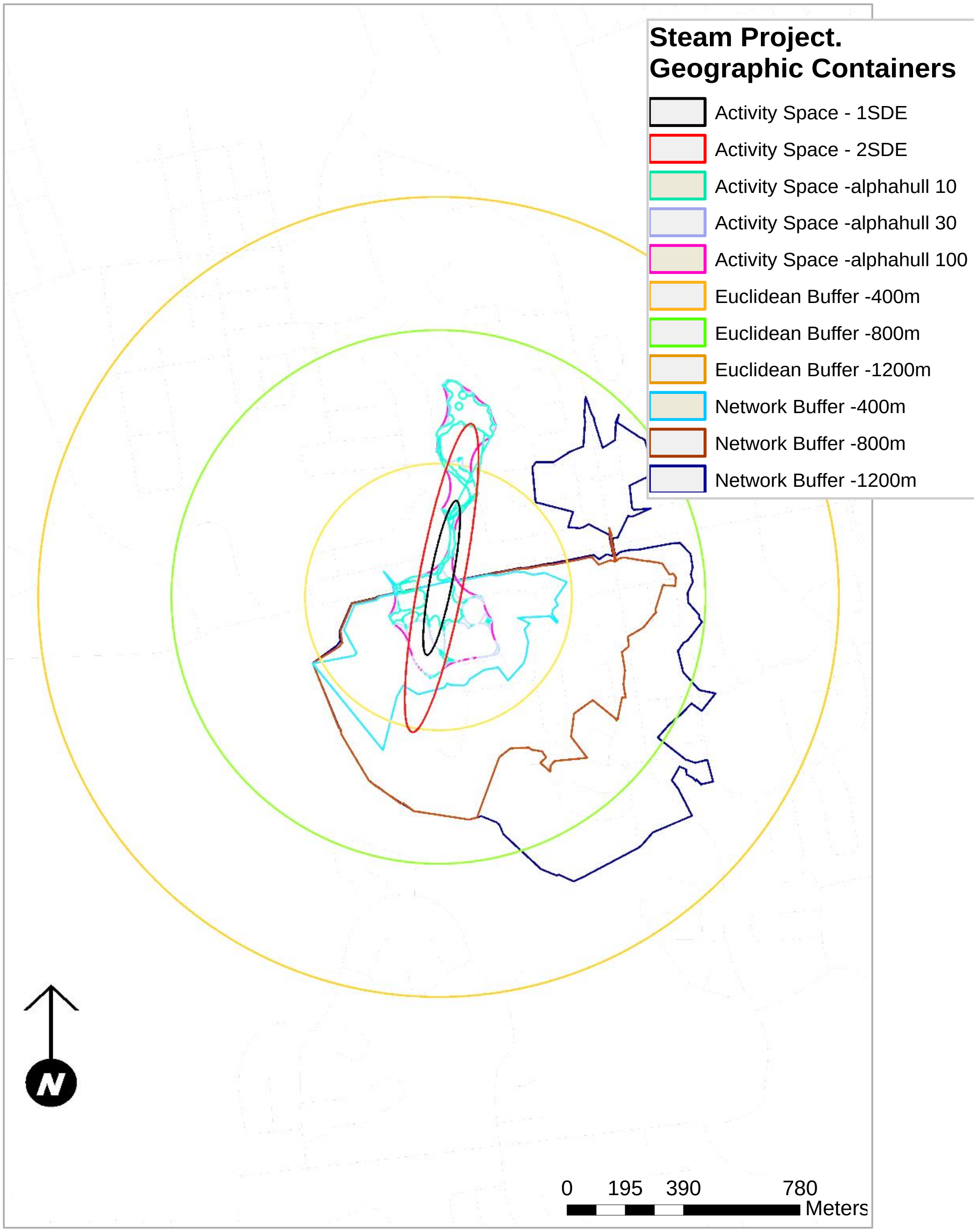

Figure 15. STEAM project – Overlay of the Geographic Containers

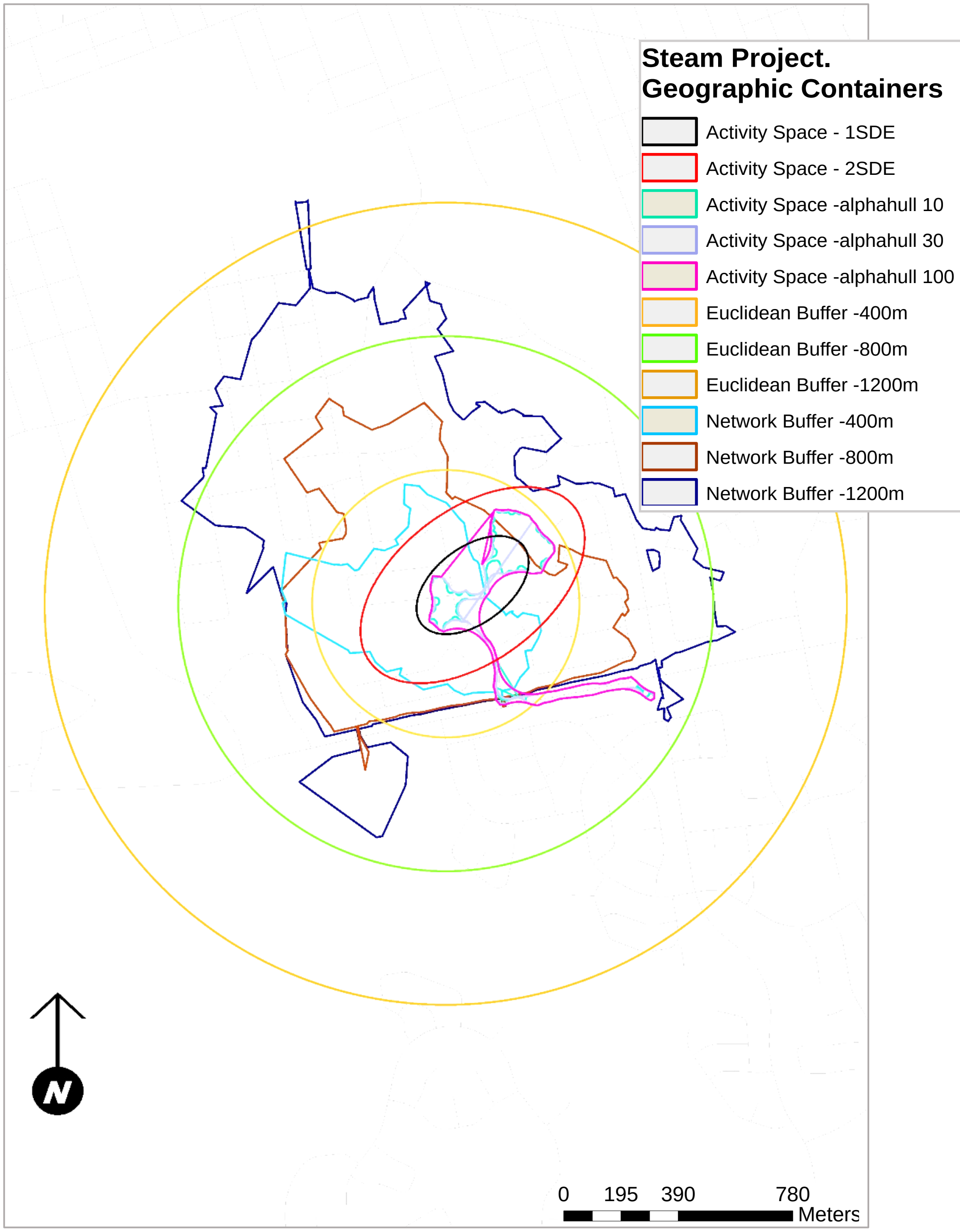

Figure 16. STEAM project – Overlay of the Geographic Containers

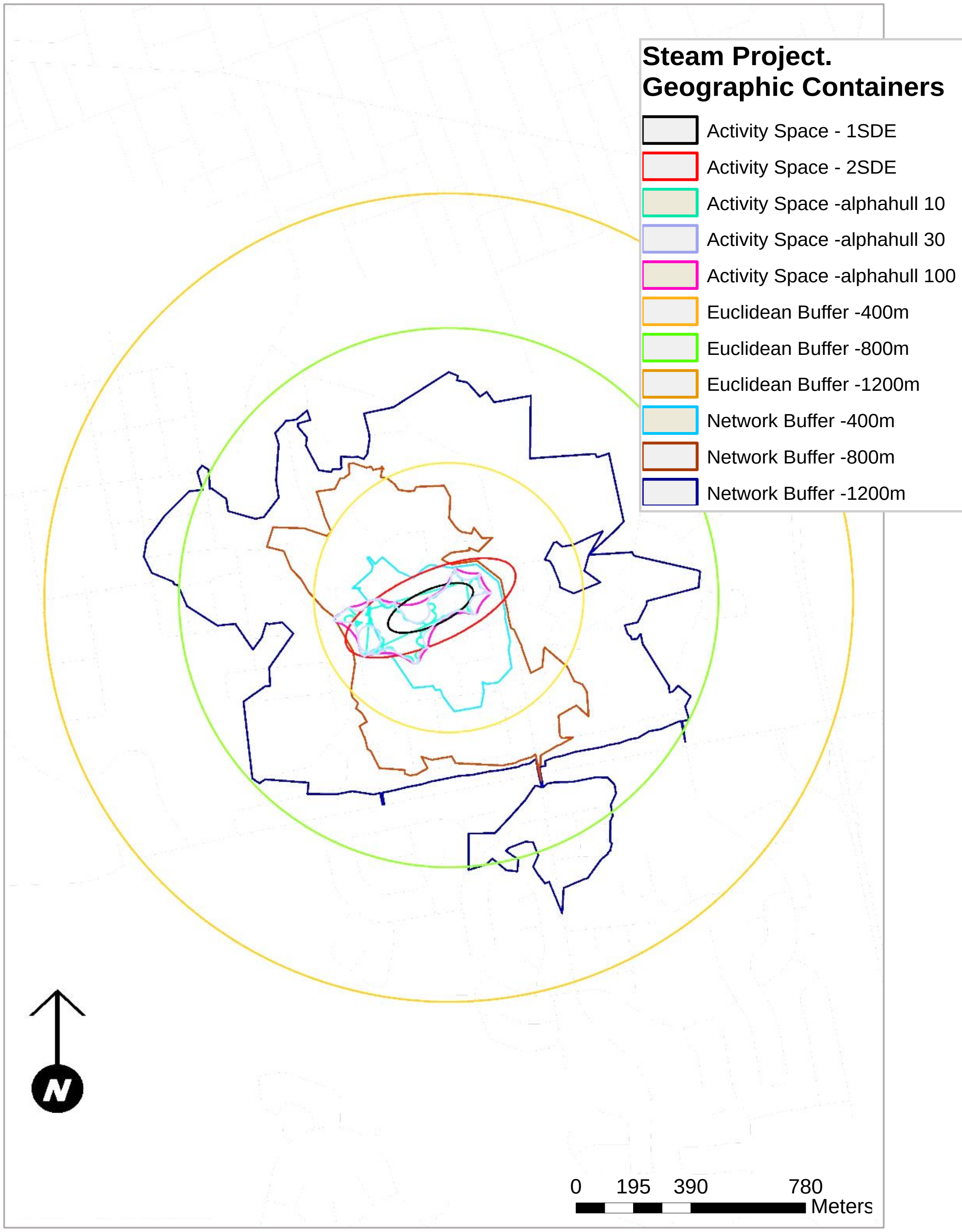

Figure 17. STEAM project – Overlay of the Geographic Containers

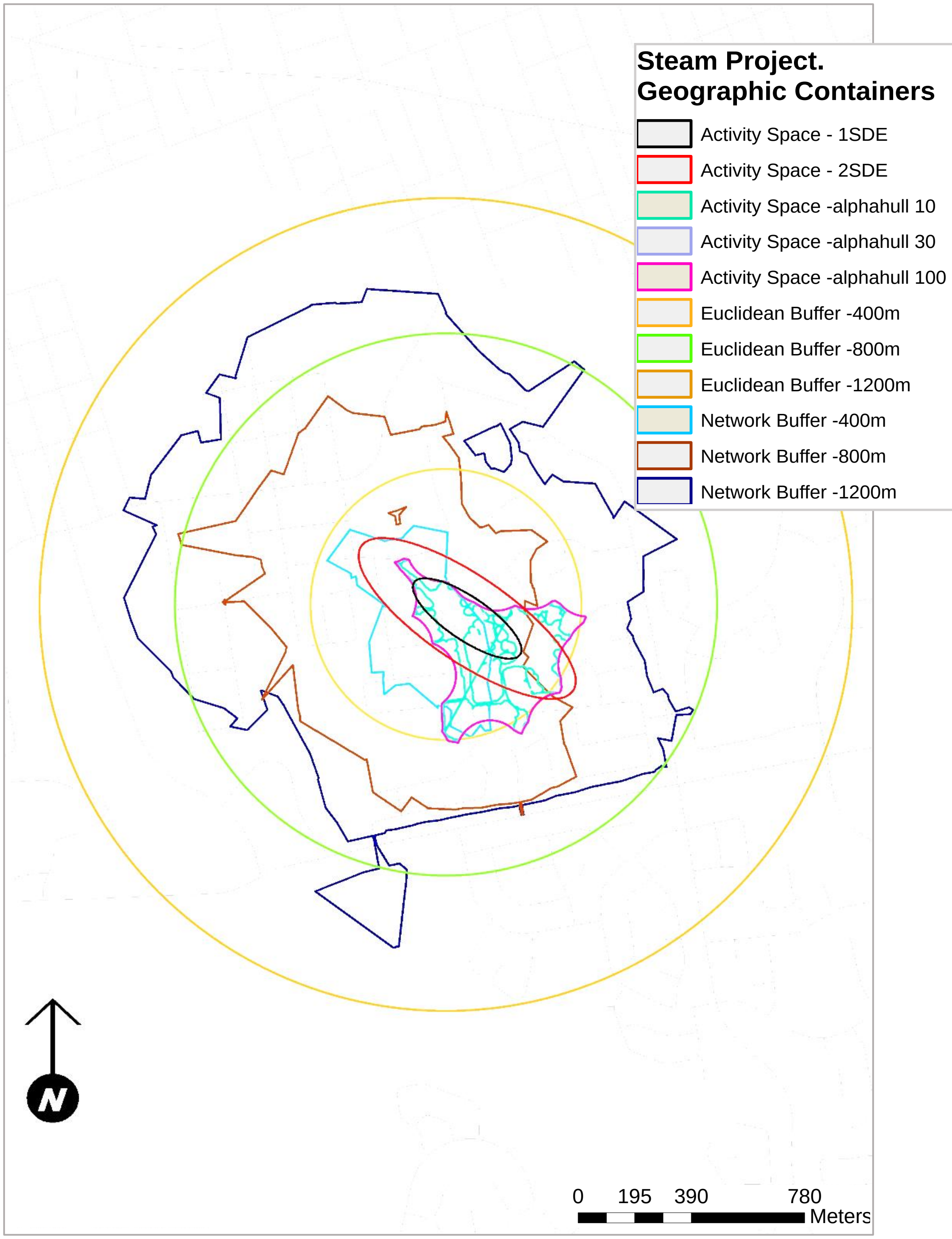

Figure 18. STEAM project – Overlay of the Geographic Containers

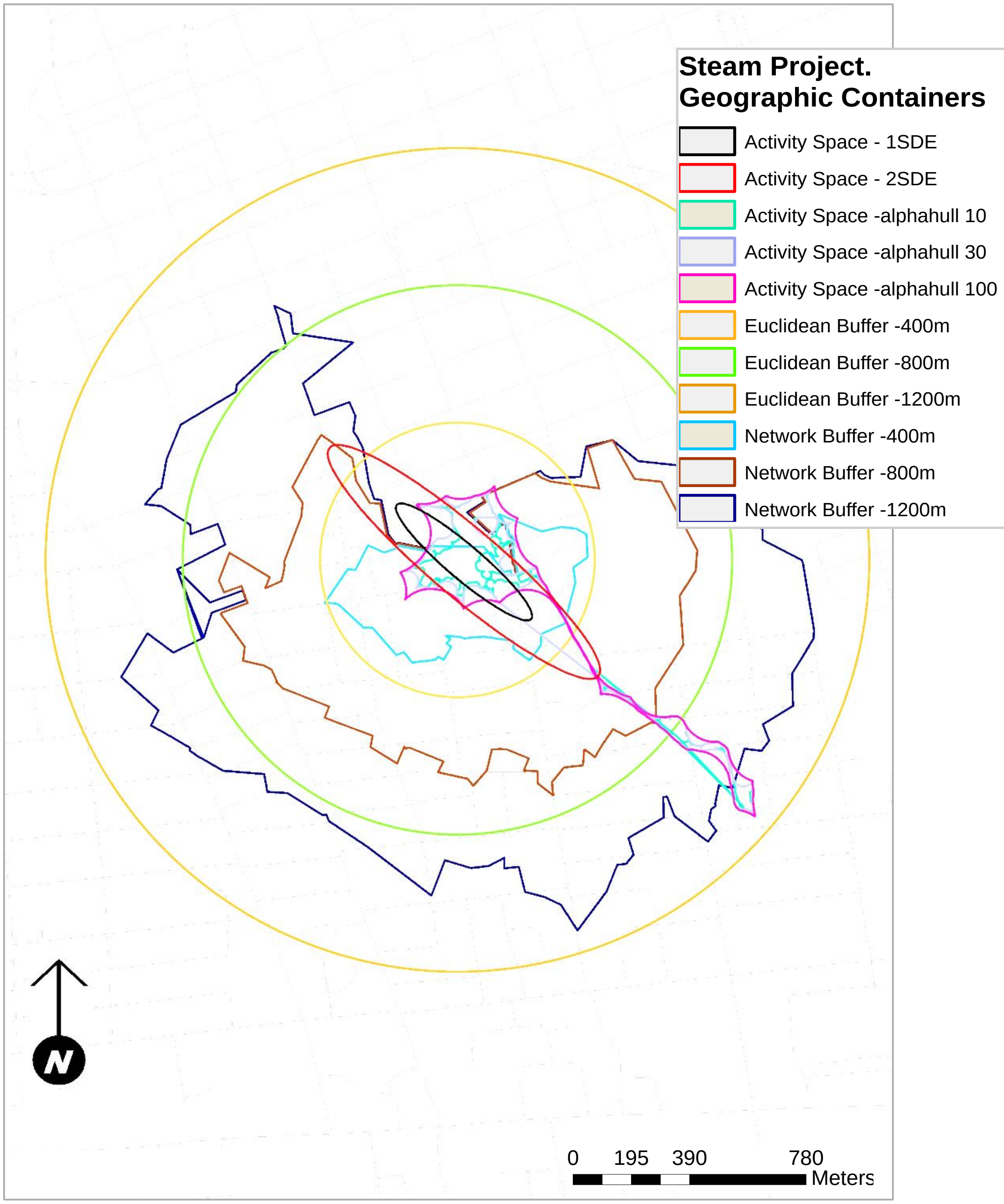

Figure 19. STEAM project – Overlay of the Geographic Containers

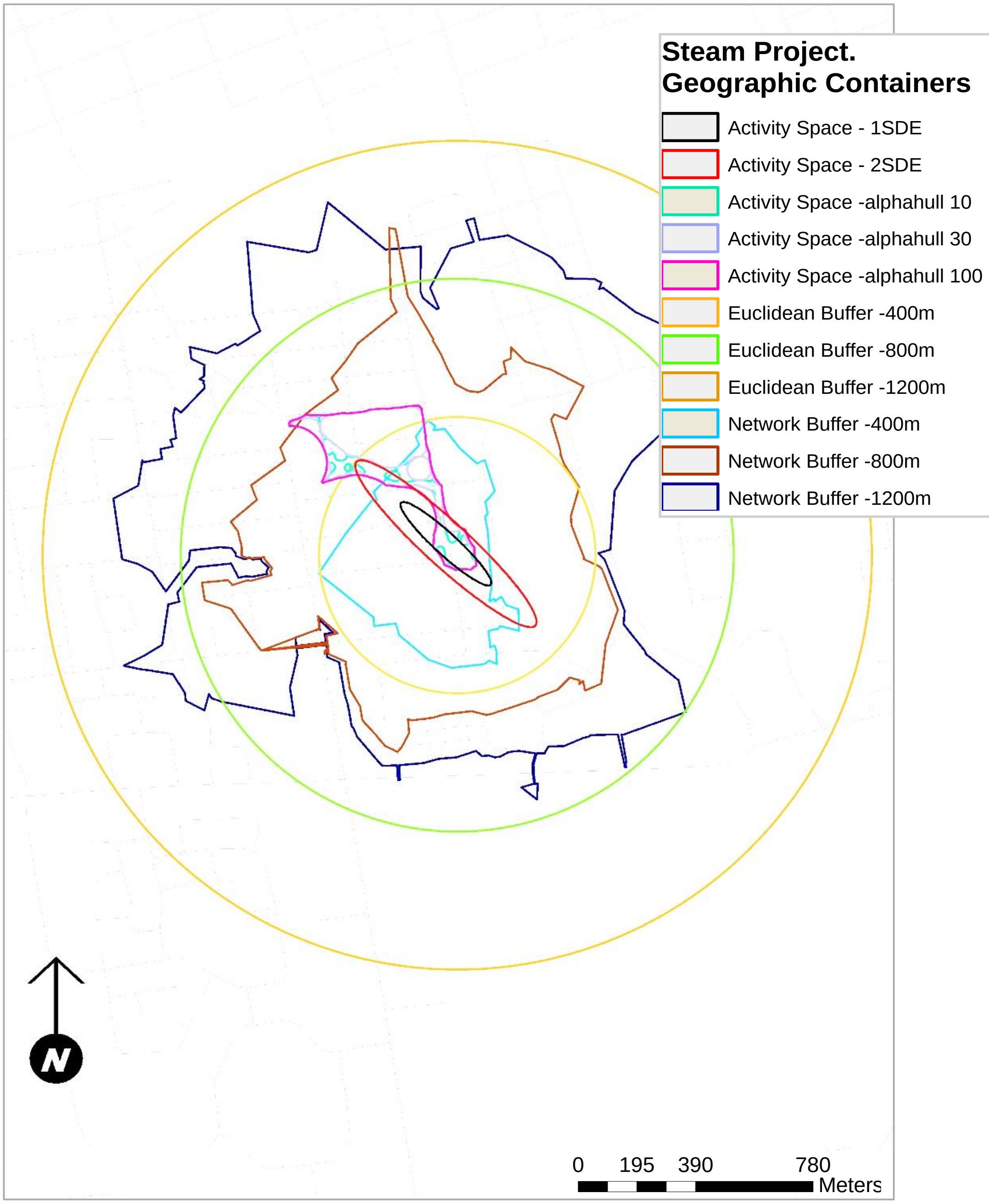

Figure 20. STEAM project – Overlay of the Geographic Containers

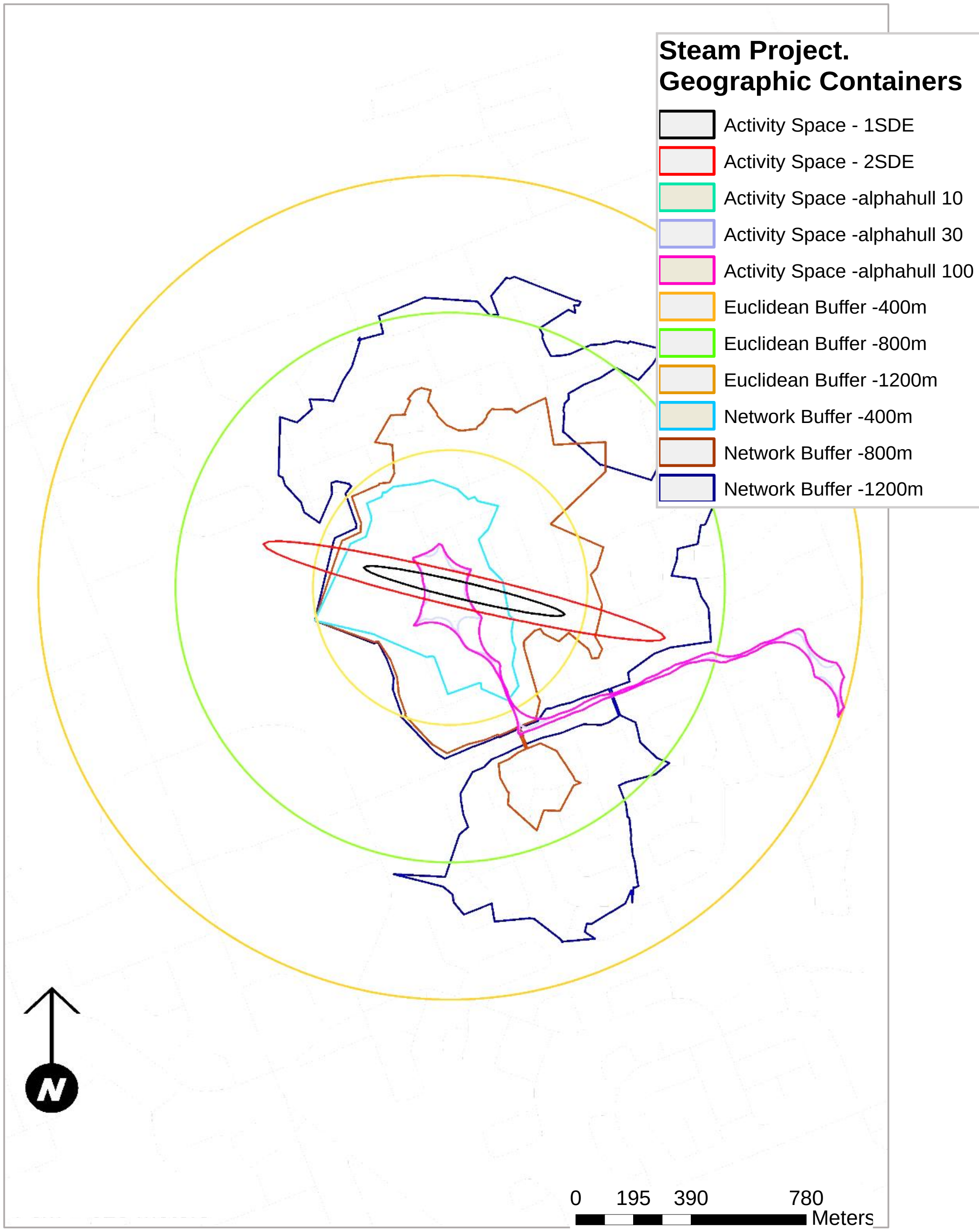

Figure 21. STEAM project – Overlay of the Geographic Containers

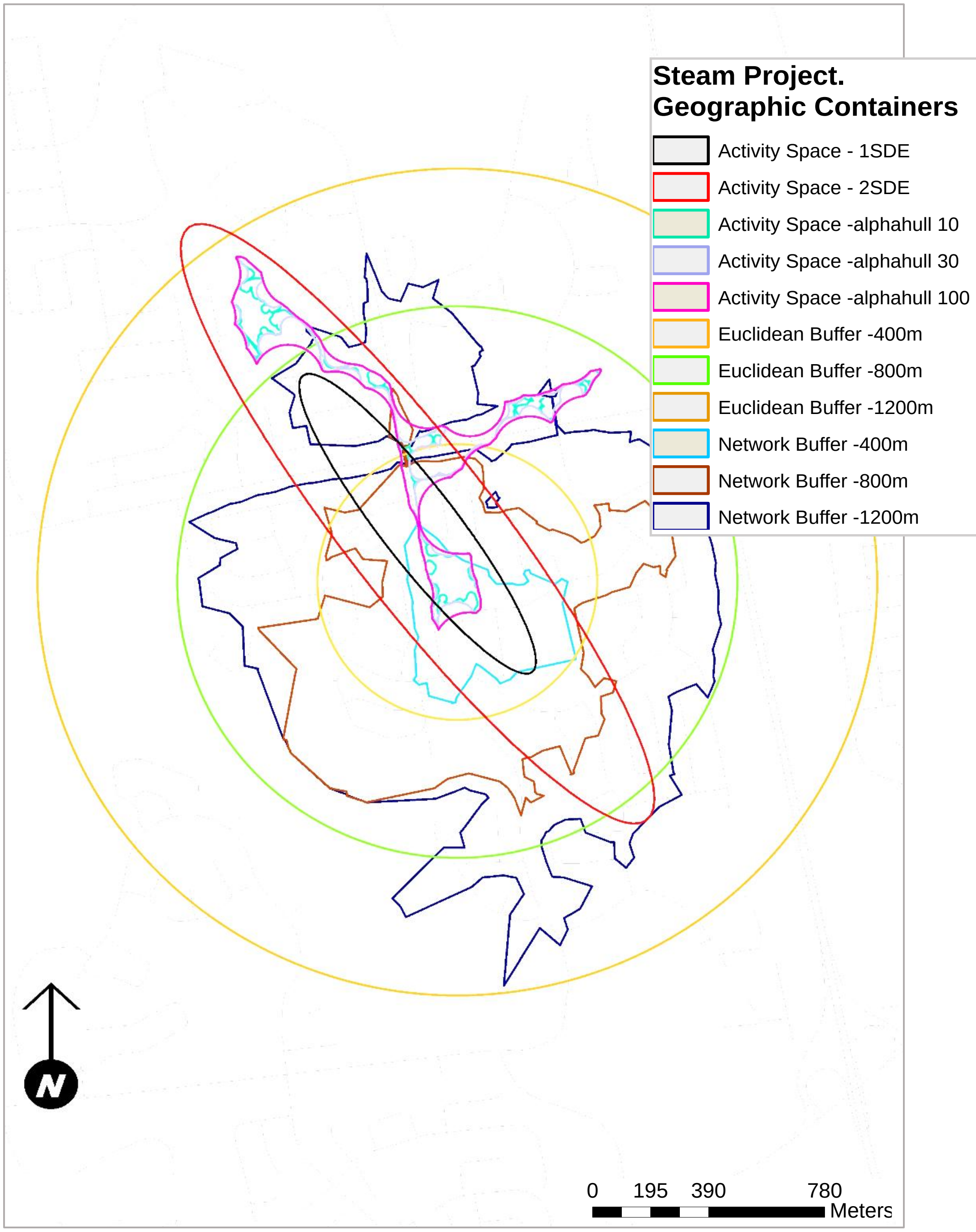

Figure 22. STEAM project – Overlay of the Geographic Containers

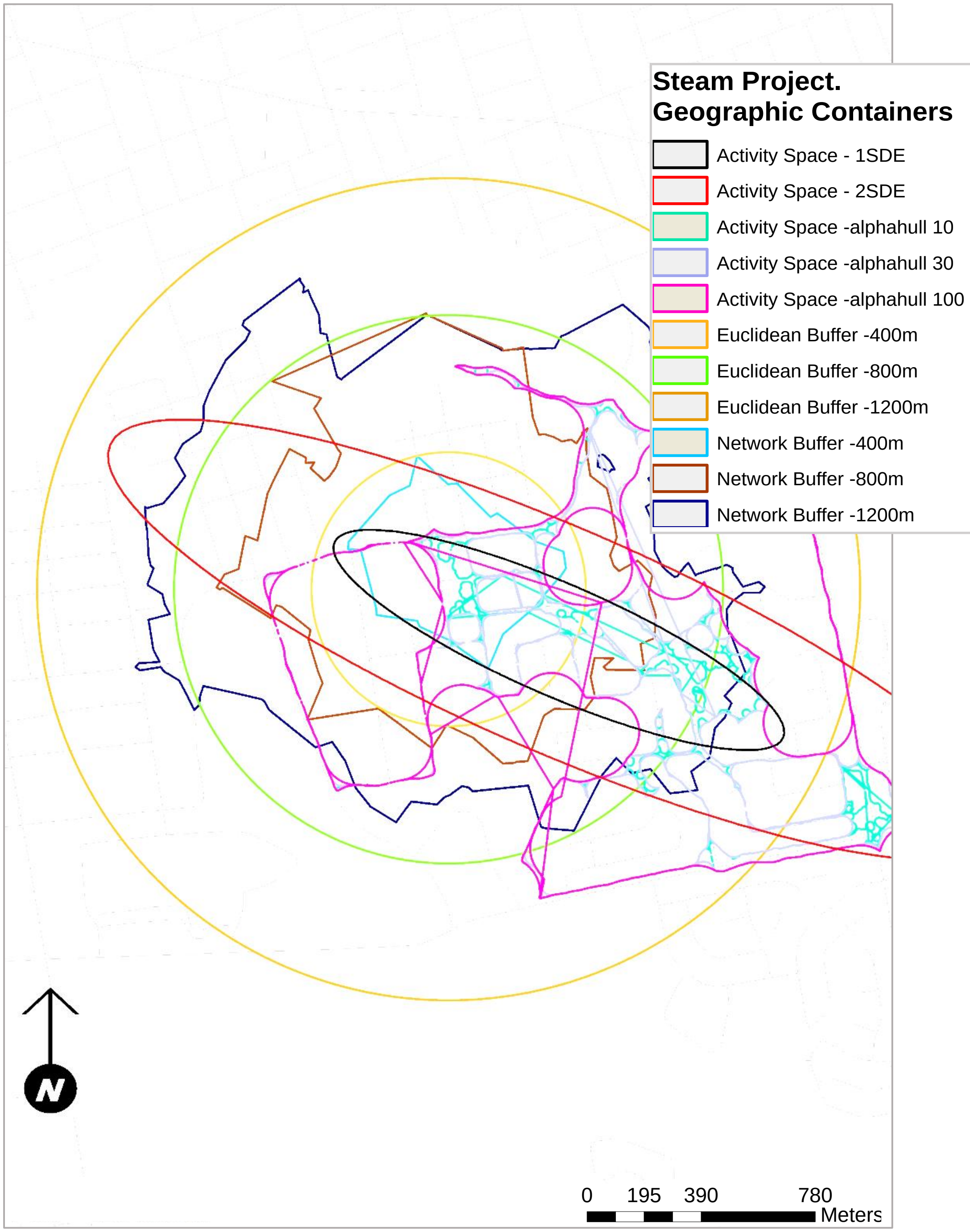

Figure 23. STEAM project – Overlay of the Geographic Containers

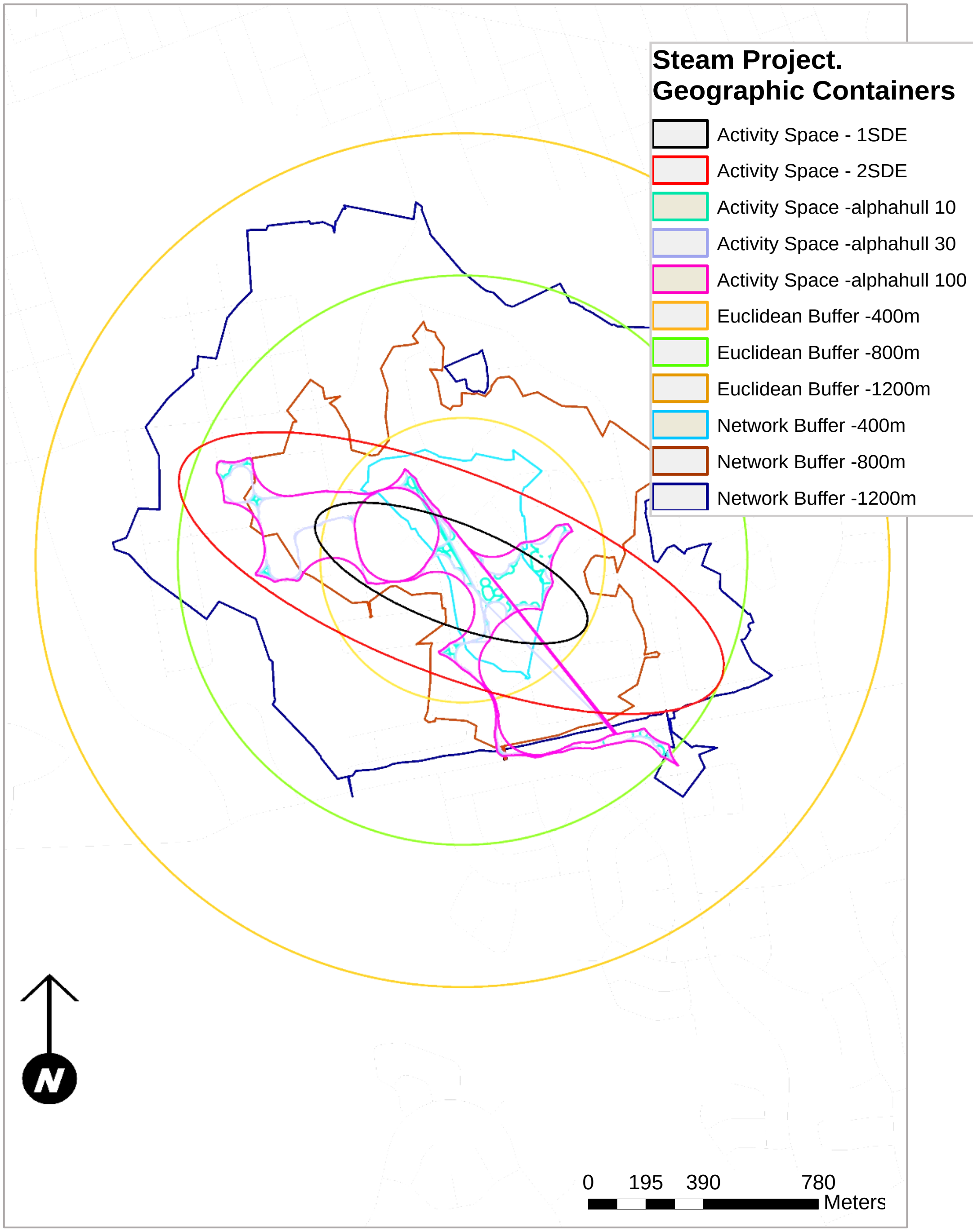

Figure 24. STEAM project – Overlay of the Geographic Containers

Similar to what was observed after visual inspection of the three α-hull based activity spaces, there is a great deal of variation in the shape and location of the SDE, α-hulls, and network buffer geographic containers. It is interesting to note that not only are the activity spaces all considerably smaller than the residentially-based containers, but they often extent outside the scope of the network buffers and even some of the 400 m and 800 m Euclidean buffers.

Network buffers, too, are, as expected, smaller than Euclidean buffers and do not overlap with the 400 m and 800 m buffers. Something that was not anticipated is the divergence between the α-hull and the Standard Deviational ellipse geographic containers. SDE ellipses have been regarded as highly appropriate methods to derive local environments, particularly for survey-based locational information. However, the various maps included in Figure 13 through 17 (inclusive) indicate that more often than not, SDE containers do not overlap.

Thus far, the analysis points to the low overlap between Euclidean, Network and SDE geographic containers and each of the α-hull containers derived from children's actual GPS tracks. The question then is whether, and to what degree, these container discrepancies affect the measurement of the number of restaurants, supermarkets, fast-food outlets, convenience stores and total number of unhealthy outlets. Table 2 to 4 present the partial correlation coefficients across geographic containers for convenience stores, fast food restaurants, supermarkets and full service restaurants, displaying only those correlations that appear statistically significant.

The three α-hull containers only appear significantly correlated to the various residentially-based containers (Euclidean and network buffers) for the food environment measure corresponding to convenience stores, but the magnitude of the association remains below 0.20. Additionally, for the partial correlations between the food outlet measures corresponding to the α-hull and SDE containers, the results point to mostly moderate to strong significant associations, with low correlations only observed for the count of convenience stores. Likewise, the various Euclidean and Network buffers display overall significant correlations with each other. However, when comparing the 400 m and 800 m Euclidean and Network containers, there is only evidence of a small significant correlation for the convenience store outlets.

Table 2. Partial Correlation Coefficients across Geographic Containers –Convenience Stores

	Activity Space - alphahull 10	Activity Space - alphahull 30	Activity Space - alphahull 100	Activity Space - 2 SDE	Activity Space - 1 SDE	Euclidean Buffer - 400 m	Euclidean Buffer - 800 m	Euclidean Buffer - 1200 m	Euclidean Buffer - 1600 m	Network Buffer- 400 m	Network Buffer- 800 m	Network Buffer- 1200 m
Activity Space - alphahull 30	0.66											
Activity Space - alphahull 100	0.49	0.76										
Activity Space - 2 SDE	0.28	0.40	0.52									
Activity Space - 1 SDE	0.19	0.25	0.34	0.64								
Euclidean Buffer -400 m												
Euclidean Buffer -800 m	0.16					0.59						
Euclidean Buffer -1200 m	0.17	0.16	0.16	0.16		0.53	0.82					
Euclidean Buffer -1600 m		0.16	0.17	0.18		0.48	0.70	0.91				
Network Buffer- 400 m							0.17	0.30	0.33			
Network Buffer- 800 m						0.19	0.25	0.37	0.39	0.90		
Network Buffer- 1200 m	0.20	0.18	0.19	0.19		0.26	0.34	0.41	0.40	0.36	0.60	
Network Buffer- 1600 m	0.18		0.17	0.20		0.24	0.37	0.46	0.45	0.42	0.63	0.89

Table 3. Partial Correlation Coefficients across Geographic Containers –Fast-food Outlets

	Activity Space - alphahull 10	Activity Space - alphahull 30	Activity Space - alphahull 100	Activity Space - 2 SDE	Activity Space - 1 SDE	Euclidean Buffer - 400 m	Euclidean Buffer - 800 m	Euclidean Buffer - 1200 m	Euclidean Buffer - 1600 m	Network Buffer- 400 m	Network Buffer- 800 m	Network Buffer- 1200 m
Activity Space - alphahull 30	0.39											
Activity Space - alphahull 100	0.29	0.73										
Activity Space - 2 SDE	0.29	0.75	0.60									
Activity Space - 1 SDE	0.16	0.80	0.58	0.89								
Euclidean Buffer -400 m												
Euclidean Buffer -800 m						0.72						
Euclidean Buffer -1200 m						0.50	0.74					
Euclidean Buffer -1600 m						0.38	0.58	0.87				
Network Buffer- 400 m								0.16	0.22			
Network Buffer- 800 m								0.19	0.24	0.87		
Network Buffer- 1200 m							0.22	0.23	0.22	0.26	0.56	
Network Buffer- 1600 m							0.22	0.26	0.25	0.34	0.56	0.81

Table 4. Partial Correlation Coefficients across Geographic Containers –Supermarkets

	Activity Space - alphahull 10	Activity Space - alphahull 30	Activity Space - alphahull 100	Activity Space - 2 SDE	Activity Space - 1 SDE	Euclidean Buffer - 400 m	Euclidean Buffer - 800 m	Euclidean Buffer - 1200 m	Euclidean Buffer - 1600 m	Network Buffer- 400 m	Network Buffer- 800 m	Network Buffer- 1200 m
Activity Space - alphahull 30	0.66											
Activity Space - alphahull 100	0.48	0.80										
Activity Space - 2 SDE												
Activity Space - 1 SDE	0.18			0.52								
Euclidean Buffer -400 m												
Euclidean Buffer -800 m						0.49						
Euclidean Buffer -1200 m						0.23	0.62					
Euclidean Buffer -1600 m							0.42	0.75				
Network Buffer-400 m								0.17	0.25			
Network Buffer-800 m								0.23	0.27	0.84		
Network Buffer-1200 m								0.23	0.21	0.27	0.50	
Network Buffer-1600 m							0.24	0.33	0.35	0.43	0.57	0.70

Table 5. Partial Correlation Coefficients across Geographic Containers –Restaurants

	Activity Space - alphahull 10	Activity Space - alphahull 30	Activity Space - alphahull 100	Activity Space - 2 SDE	Activity Space - 1 SDE	Euclidean Buffer - 400 m	Euclidean Buffer - 800 m	Euclidean Buffer - 1200 m	Euclidean Buffer - 1600 m	Network Buffer- 400 m	Network Buffer- 800 m	Network Buffer- 1200 m
Activity Space - alphahull 30	0.49											
Activity Space - alphahull 100	0.29	0.66										
Activity Space - 2 SDE	0.29	0.55	0.52									
Activity Space - 1 SDE	0.30	0.61	0.58	0.77								
Euclidean Buffer -400 m												
Euclidean Buffer -800 m						0.78						
Euclidean Buffer -1200 m						0.63	0.85					
Euclidean Buffer -1600 m						0.51	0.70					
Network Buffer-400 m												
Network Buffer-800 m				0.17			0.18	0.20	0.86			
Network Buffer-1200 m				0.22		0.17	0.30	0.29	0.33	0.62		
Network Buffer-1600 m				0.17		0.18	0.29	0.29	0.33	0.53	0.78	

Figure 25 displays the distribution of food outlets across geographic container and food outlet type. For children in our sample, the Euclidean buffers larger than 400 m greatly overestimate the number of food outlets that are actually located in the activity spaces of children.

Looking at the breakdown of food outlet type, children have, on average, more fast-food restaurants than any other type of outlet, something that is consistently observed across all geographic containers. For instance, out of 100 food outlets in a child's local food environment for our sample, between 40 and 46 would be fast-food outlets, 23 to 39 convenience stores, 15 to 24 would be full service restaurants, 2 to 3 supermarkets, and 1 to 3 would be farmer's markets or fresh produce outlets. It is worth noting that the share of convenience stores out of the total number of outlets is larger only for the α-hull = 10 container.

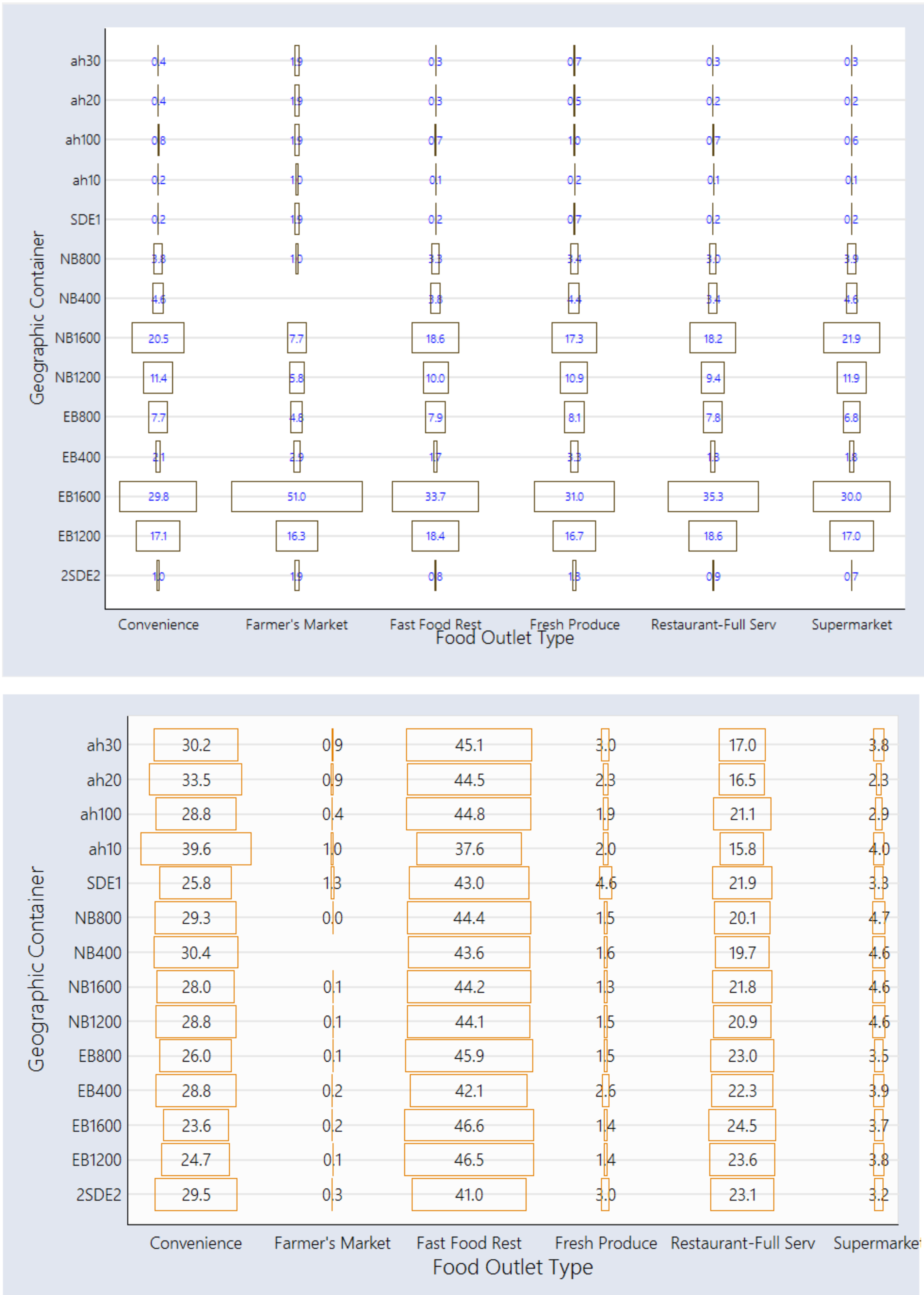

Figure 25. Trellis Plot of the Distribution of Food Outlets across Geographic Container (Top) and between Geographic Containers (Bottom)

Table 6 displays the matrix of kappa statistics for the number of unhealthy food outlets (fast-food restaurants + convenience stores) for the thirteen geographic containers. There is moderate to substantial agreement among the α -hulls activity space measures (kappa values: 0.5 - 0.7), fair to moderate agreement between the α -hulls and the SDE activity space containers (kappa values: 0.3 - 0.5), slight to fair agreement between the SDE activity space containers and the Euclidean and network buffers (kappa values: 0.0 – 0.22), but only slight agreement, at the most, between α -hulls and any of the Euclidean and network buffer containers (kappa values: 0.0 – 0.2). It should be noted that, similar to previous studies, the agreement between Euclidean and network buffers of the same size have only slight agreement.

Table 6. Kappa Statistics for Agreement across Geographic Containers -Quartiles of Unhealthy Food Outlets

	AS α-hull 10	AS α-hull 30	AS α-hull 100	AS-SDE2	AS-SDE1	EB-400m	EB-800m	EB-1200m	EB-1600m	NB-400m	NB-800m	NB-1200m
AS α-hull 30	0.74 ***											
AS α-hull 100	0.50 ***	0.70 ***										
AS- SDE2	0.32 ***	0.44 ***	0.51 ***									
AS- SDE1	0.32 ***	0.33 ***	0.35 ***	0.55 ***								
EB-400m	0.12 ***	0.18 ***	0.19 ***	0.22 ***	0.12 ***							
EB-800m	0.06 ***	0.07 ***	0.08 ***	0.10 ***	0.05 ***	0.28 ***						
EB-1200m	0.06 ***	0.08 ***	0.12 ***	0.11 ***	0.05 ***	0.22 ***	0.40 ***					
EB-1600m	0.06 ***	0.08 ***	0.12 ***	0.12 ***	0.06 ***	0.19 ***	0.26 ***	0.55 ***				
NB-400m	0.09 ***	0.12 ***	0.17 ***	0.20 ***	0.10 ***	0.14 ***	0.11 ***	0.14 ***	0.13 ***			
NB-800m	0.06 ***	0.08 ***	0.12 ***	0.13 ***	0.04 *	0.15 ***	0.15 ***	0.16 ***	0.16 ***	0.45 ***		
NB-1200m	0.04 **	0.05 **	0.06 **	0.07 ***	0.01	0.17 ***	0.13 ***	0.12 ***	0.10 ***	0.21 ***	0.49 ***	
NB-1600m	0.03 *	0.03 *	0.06 ***	0.08 ***	0.01	0.12 ***	0.13 ***	0.14 ***	0.12 ***	0.19 ***	0.36 ***	0.54 ***

Note: * p< 0.05 ** p< 0.01 *** p<0.001.
EB: Euclidean Buffer – **NB**: Network Buffer– **AS-SDE1:** Activity Space- 1 SD ellipse – **AS-SDE2:** Activity Space- 2 SD ellipse –
AS α -hull: Activity Space - α -hull

Table 7 to Table 10 present kappa statistics broken down by food outlet type. Table 7 displays that the agreement between measures of supermarket remain moderate to substantial between α -hull activity space containers, but it is much lower for the measures between α -hulls and SDE containers, and α -hulls and the Euclidean and network buffer containers, and considerably higher between the same distance Euclidean and network buffer containers which are now indicating fair to moderate agreement.

Table 7. Kappa Statistics for Agreement across Geographic Containers -Quartiles of Supermarkets

	AS α-hull 10	AS α-hull 30	AS α-hull 100	AS-SDE2	AS-SDE1	EB-400m	EB-800m	EB-1200m	EB-1600m	NB-400m	NB-800m	NB-1200m
AS α-hull 30	0.61 ***											
AS α-hull 100	0.44 ***	0.78 ***										
AS- SDE2	0.11 ***	0.07	0.05									
AS- SDE1	0.24 ***	0.14 ***	0.10 *	0.46 ***								
EB-400m	0.07 ***	0.04	0.06	0.20 ***	0.07 ***							
EB-800m	0.02 ***	0.04 ***	0.05 ***	0.04 ***	0.01 *	0.21 ***						
EB-1200m	0.00	0.00	0.01	0.03 ***	0.01 *	0.06 ***	0.26 ***					
EB-1600m	0.01 *	0.02 *	0.02 *	0.03 **	0.01 *	0.07 ***	0.18 ***	0.28 ***				
NB-400m	0.07 **	0.05	0.10 **	0.10 **	0.07 **	0.41 ***	0.12 ***	0.06 ***	0.12 ***			
NB-800m	0.05 **	0.07 *	0.12 ***	0.12 ***	0.05 **	0.50 ***	0.27 ***	0.13 ***	0.19 ***	0.63 ***		
NB-1200m	0.01	0.02 *	0.04 **	0.05 ***	0.02 *	0.18 ***	0.57 ***	0.21 ***	0.15 ***	0.16 ***	0.34 ***	
NB-1600m	0.01 *	0.03 **	0.05 ***	0.03 *	0.01 *	0.09 ***	0.39 ***	0.23 ***	0.26 ***	0.19 ***	0.32 ***	0.59 ***

Note: * p< 0.05 ** p< 0.01 *** p<0.001.
EB: Euclidean Buffer – **NB**: Network Buffer– **AS-SDE1:** Activity Space- 1 SD ellipse – **AS-SDE2:** Activity Space- 2 SD ellipse –
AS α-hull: Activity Space - α -hull

Table 8. Kappa Statistics for Agreement across Geographic Containers -Quartiles of Fast-food Outlets

	AS α-hull 10	AS α-hull 30	AS α-hull 100	AS-SDE2	AS-SDE1	EB-400m	EB-800m	EB-1200m	EB-1600m	NB-400m	NB-800m	NB-1200m
AS α-hull 30	0.61 ***											
AS α-hull 100	0.36 ***	0.65 ***										
AS- SDE2	0.22 ***	0.35 ***	0.40 ***									
AS- SDE1	0.24 ***	0.15 ***	0.21 ***	0.51 ***								
EB-400m	0.08 ***	0.17 ***	0.22 ***	0.25 ***	0.13 ***							
EB-800m	0.03 *	0.05 ***	0.07 ***	0.09 ***	0.03 **	0.31 ***						
EB-1200m	0.03 **	0.05 ***	0.07 ***	0.08 ***	0.04 ***	0.18 ***	0.35 ***					
EB-1600m	0.03 **	0.05 ***	0.08 ***	0.07 ***	0.03 ***	0.14 ***	0.27 ***	0.51 ***				
NB-400m	0.05 *	0.08 **	0.13 ***	0.11 **	0.08 **	0.36 ***	0.20 ***	0.14 ***	0.12 ***			
NB-800m	0.02	0.05 *	0.09 ***	0.09 ***	0.04 *	0.32 ***	0.38 ***	0.23 ***	0.19 ***	0.41 ***		
NB-1200m	0.02 *	0.03 *	0.05 **	0.05 **	0.01	0.19 ***	0.38 ***	0.26 ***	0.15 ***	0.14 ***	0.42 ***	
NB-1600m	0.01	0.02	0.05 **	0.04 **	0.01	0.14 ***	0.36 ***	0.36 ***	0.27 ***	0.14 ***	0.28 ***	0.48 ***

Note: * p< 0.05 ** p< 0.01 *** p<0.001.
EB: Euclidean Buffer – **NB**: Network Buffer– **AS-SDE1:** Activity Space- 1 SD ellipse – **AS-SDE2:** Activity Space- 2 SD ellipse –
AS α-hull: Activity Space - α -hull

Table 8 shows the kappa measures of agreement for the quartile counts of fast-food outlets. Slightly lower kappa values are observed between the α -hulls containers, while the agreement between SDE and α -hull activity space containers, and the SDE and the residentially-based buffers are higher than those for supermarkets. Agreement between Euclidean and network buffer containers remained fair.

Table 9. Kappa Statistics for Agreement across Geographic Containers -Quartiles of Convenience Stores

	AS α-hull 10	AS α-hull 30	AS α-hull 100	AS-SDE2	AS-SDE1	EB-400m	EB-800m	EB-1200m	EB-1600m	NB-400m	NB-800m	NB-1200m
AS α-hull 30	0.72 ***											
AS α-hull 100	0.48 ***	0.72 ***										
AS- SDE2	0.32 ***	0.49 ***	0.58 ***									
AS- SDE1	0.32 ***	0.39 ***	0.40 ***	0.53 ***								
EB-400m	0.12 ***	0.20 ***	0.24 ***	0.28 ***	0.14 ***							
EB-800m	0.03 **	0.06 ***	0.07 ***	0.08 ***	0.04 ***	0.25						
EB-1200m	0.04 ***	0.06 ***	0.10 ***	0.11 ***	0.04 ***	0.20	0.45 ***					
EB-1600m	0.07 ***	0.09 ***	0.12 ***	0.13 ***	0.06 ***	0.22	0.28 ***	0.54 ***				
NB-400m	0.09 ***	0.14 ***	0.16 ***	0.20 ***	0.09 ***	0.45	0.18 ***	0.16 ***	0.18 ***			
NB-800m	0.07 ***	0.09 ***	0.12 ***	0.15 ***	0.04 **	0.32	0.35 ***	0.24 ***	0.24 ***	0.41 ***		
NB-1200m	0.06 ***	0.07 ***	0.09 ***	0.10 ***	0.03 **	0.26	0.44 ***	0.26 ***	0.22 ***	0.21 ***	0.47 ***	
NB-1600m	0.05 ***	0.06 ***	0.09 ***	0.10 ***	0.03 **	0.18	0.38 ***	0.38 ***	0.30 ***	0.19 ***	0.35 ***	0.56 ***

Note: * p< 0.05 ** p< 0.01 *** p<0.001.
EB: Euclidean Buffer – **NB**: Network Buffer– **AS-SDE1:** Activity Space- 1 SD ellipse – **AS-SDE2:** Activity Space- 2 SD ellipse –
AS α -hull: Activity Space - α -hull

As can be seen in Table 9, agreement between the α -hulls and the SDE containers are the highest for the measures of convenience stores relative to other food outlets, with kappa values showing fair to moderate agreement (0.32-0.58). Similarly, agreement between α -hulls and the Euclidean buffers is higher for convenience stores relative to other food outlets, although it remains as slight agreement with the exception of the agreement between α -hull=100 and the EB 400 containers that reached fair agreement (0.24). Kappa values also indicate higher agreement for convenience stores measures between Euclidean and network buffers with the same distance. Table 10 shows similar, but slightly lower agreement between Euclidean and network buffers, α-hulls and SDE, and α-hulls and Euclidean and network buffers.

All tables indicate that among all the residentially-based buffers, the 400 m Euclidean buffer had the highest agreement with all the activity space containers. This finding is unexpected to some degree, as network buffers are assumed to better mimic individual's use of space by incorporating the street network of their local neighbourhood. More importantly, across all food outlet types, there is lower agreement than initially expected between α-hulls-based food environment and the various geographic containers used in the literature. Again, since α-hulls are based on actual use of space captured by GPS tracks, the modest kappa statistics indicate that using residentially-based geographic containers and to some extent the SDE activity spaces, can result in over-estimation, or under-estimation, of children's local food environment.

Table 10. Kappa Statistics for Agreement across Geographic Containers -Restaurants-

	AS α-hull 10	AS α-hull 30	AS α-hull 100	AS-SDE2	AS-SDE1	EB-400m	EB-800m	EB-1200m	EB-1600m	NB-400m	NB-800m	NB-1200m
AS α-hull 30	0.60 ***											
AS α-hull 100	0.34 ***	0.56 ***										
AS- SDE2	0.18 ***	0.36 ***	0.52 ***									
AS- SDE1	0.32 ***	0.22 ***	0.33 ***	0.44 ***								
EB-400m	0.08 ***	0.14 ***	0.17 ***	0.25 ***	0.11 ***							
EB-800m	0.01 *	0.04 ***	0.05 ***	0.06 ***	0.02 *	0.25 ***						
EB-1200m	0.02 *	0.05 ***	0.06 ***	0.08 ***	0.01	0.25 ***	0.40 ***					
EB-1600m	0.02 **	0.04 ***	0.06 ***	0.07 ***	0.01	0.18 ***	0.28 ***	0.46 ***				
NB-400m	0.06 **	0.13 ***	0.20 ***	0.18 ***	0.10 ***	0.32 ***	0.15 ***	0.16 ***	0.14 ***			
NB-800m	0.04 **	0.06 ***	0.11 ***	0.14 ***	0.05 ***	0.40 ***	0.35 ***	0.27 ***	0.24 ***	0.45 ***		
NB-1200m	0.01	0.04 ***	0.05 **	0.07 ***	0.02 *	0.24 ***	0.49 ***	0.32 ***	0.18 ***	0.19 ***	0.39 ***	
NB-1600m	0.00	0.01	0.02	0.05 ***	0.01	0.17 ***	0.43 ***	0.33 ***	0.29 ***	0.15 ***	0.32 ***	0.53 ***

Note: * p< 0.05 ** p< 0.01 *** p<0.001.
EB: Euclidean Buffer – **NB**: Network Buffer– **AS-SDE1:** Activity Space- 1 SD ellipse – **AS-SDE2:** Activity Space- 2 SD ellipse –
AS α-hull: Activity Space - α-hull

This chapter described results of the analysis looking at the degree of similarity between various definitions of the local environment of a sample of children, and their effect on derived measures of food environment. They indicate a low level of overlap between the areas of standard Euclidean and Network buffer container and GPS-based activity space containers. Kappa statistics also provide evidence of statistical significant low agreement between each of the four food environment measures, restaurants, convenience stores, supermarkets and fast food outlets between containers. There is higher agreement between Network and Euclidean based containers, and between α-hulls and SDE containers. Inevitably, GIS analyses are based on a representation of the actual geographic space that children navigate, aiming for a balance between generalizability and granularity. However, this chapter points to non-negligible variations of food environment measures when using detailed polygons closely resembling children non-motorized movement and pre-determined buffers around their home. And as discussed in chapter 2, coarser containers based of administrative units can depart even more from the spaces intersecting children daily activities. Such variations should not be taken as an afterthought in the analysis, and the effect of the geographic container chosen should be assessed and discussed above and beyond model fit statistics.

Chapter Six: An Empirical Application of Geographic Containers to Children's BMI and Diet Outcomes

6.1. Introduction

6.1.1. The Obesity Problem

Extensive research over the last two decades consistently shows the rapid increase in childhood obesity prevalence in Canada, with a fourfold increase in obesity rates among children aged 6–11 years and more than double among adolescents aged 12–19 (Vanasse et al., 2006). More importantly, obesity prevalence for boys and girls in Canada cannot be fully accounted for by geographic or demographic characteristics (Willms et al., 2003).

Due to the sheer number of kids that are now obese or overweight, and more importantly, the compounded health risks that obese children are exposed to, childhood obesity and its yet unclear causal mechanisms have earned a prominent place in research and policy.

In addition to the financial burden already established for adult obesity prevalence (Moffatt et al., 2011), with direct costs estimated at 1.6 billion by 2001 (Pouliou & Elliott, 2010), childhood obesity is a pressing concern given its associated comorbidities during childhood and later in adulthood. Obesity in children has been linked to a host of issues like diabetes and heart disease (Ball, Geoff DC & McCargar, 2003), sleep problems (J. Liu et al., 2011), and depression (Luppino et al., 2010) during childhood, and chronic obesity (Herman et al., 2009), hypertension, heart disease, cancer (Roberts et al., 2010), osteoarthritis (Daniels, 2009) and a shorter life expectancy in adults (Abdullah et al., 2011). In addition, obesity can have an impact on cognitive outcomes and a detrimental effect on emotional well-being, with previous research showing a link between obesity and confidence or identity formation (Bisset et al., 2013; Wardle & Cooke, 2005).

6.1.2. Turning the Attention to the (Built) Environment

Children are less active now than 10 years ago (Corder,Kirsten, Corder, Sallis, Crespo, & Elder, 2011; Allison, Adlaf, Dwyer, Lysy, & Irving, 2007), dine more outside the house, consume a higher percentage of fast-food vs. healthy foods (Nielsen,Samara Joy et al., 2002), and drink more sugar-sweetened sodas than milk, water or natural juices (Wang et al., 2008) (Moubarac et al., 2012). A study in the province of Quebec, found that while only 34 percent children in the study met the recommended vegetable and fruit intake, 58 percent consume sweetened beverages every day and over 40 percent reported going at least once a week to a food establishment for a snack or a meal (Hulst et al., 2012). Ogden pointed out that Canadian children between 12 and 19 years consuming less than the recommended amount of fruits and vegetable had a higher obesity prevalence than those that met the recommendations (Ogden et al., 2011). These trends underscore the need to identify the modifiable factors behind this energy imbalance. An increasing number of studies over the past two decades have focused on the energy intake side, and a share of these studies have focused specifically on understanding how features of the local food environment translate into individual outcomes such as BMI, energy intake, food preferences, or eating behaviours.

Although researchers now agree that the built environment (BE) mediates the energy balance equation either by encouraging energy intake or discouraging energy expenditure in adults (Liu, GC et al., 2002), studies on children are less conclusive, possibly due to choice of data, outcome measurement or definition of children's environment (Kirk et al., 2010).

6.1.3. Objective of the Chapter

This chapter seeks to contribute to this literature, by providing empirical evidence about the role of the local food environment on individual outcomes for a sample of children in London, Ontario. To that end, the present analysis makes use of the different geographic containers described in the previous chapter and applies them to examining variations in BMI and dietary preferences for the same sample of children in the STEAM project. The question underlying this chapter is:

How does the local food environment influence children's dietary behaviours and BMI?

6.2. Methods

6.2.1. Outcomes

6.2.1.1. BMI

Objective measures of BMI were calculated for each child using objective height and weight measurements collected by trained STEAM project team members. As it is standard in the literature, age and gender specific body mass index (BMI[2]- z-scores) were generated from equations provided by the WHO Stata macro. Age was calculated in months as the middle point of their age according to date of birth information. Z-score calculations are based on the most current World Health Organization growth curves[3] (WHO growth reference) (De Onis & Lobstein, 2010; Tremblay et al., 2002) (Gilliland et al., 2012). The resulting z-scores represent the number of standard deviations of a child's BMI above or below the reference mean for the child's age and sex. Binary variables for overweight and obese were derived from the z-scores that were > 1SD or > 2SD respectively.

6.2.1.2. Dietary Outcome

An additional dietary outcome was also included in this second analysis which employed the geographic containers addressed in the previous chapter. The STEAM protocol includes a children's diary where they record their activities, time, and location, for various time blocks during each day of the project. Diary data is later entered, cleaned, and processed in SQL and MS-Access and coded following STEAM protocols. Relevant to this analysis, are the coded fields regarding whether children ate something on their way to and from school, along with the type of place the stop took place. The database was queried to create a "visit food outlet" variable. The variable was defined as a binary outcome (1=Yes, 0= No), with 1 assigned only for food stops

[3] WHO growth reference curves are based on samples of children selected to represent optimal growth (WHO, 2007)

that took place at a fast-food restaurant or convenience store, following the food outlet classification developed in the previous chapter.

6.2.2. Statistical Analysis

Mann‑*Whitney U* tests were used to test the correlation between obese, overweight, and normal weight participants, as well as between participants reporting having visited a fast-food outlet or convenience store and those who did not. This test is a nonparametric methods designed to detect whether two independent samples come from the same distribution, and assumes that the variable under consideration was measured on at least an ordinal (rank order) scale but does not assume that the dependent variable is a normally distributed interval variable, as it is in our case. The interpretation of the test is essentially identical to the interpretation of the result of a t-test for independent samples, except that the U test is computed based on rank sums rather than means. The U test is the most powerful (or sensitive) nonparametric alternative to the t-test for independent samples. In all statistical analyses, $P < 0.05$ was considered statistically significant. Data analyses were performed using Stata 12.0 (StataCorp, College Station, TX)

To evaluate the influence of the choice of geographic container on the association between the local food environment and children's BMI and dietary behaviours, a logistic regression model with robust variance estimators was also carried out. The resulting coefficients would indicate the contribution and statistical significance of each type of food outlet on the odds of visiting a food stores or being obese, above and beyond that of the others. Results are provided separately by the various geographic containers with the exception of the 1200 m and 1600 m residence-based buffers since the previous analysis pointed out the extreme differences with the actual extent of children's local environment in our sample. All analyses were conducted using STATA Version 10.1 (StataCorp, College Station, TX, USA).

Covariates

The analysis includes controls for age, gender, and unemployment rate of the child residential postal code as a proxy for socio-economic status –SES-.

6.1. Results

Table 11. Summary Statistics of Food Environment differences

`	Overweight (%)	Obese (%)	Visit Food Outlet (%)	DA Unempl. Rate Mean	SD
Age					
≤ 10 years old (n=69)	15.53	19.40	16.19	6.18	4.02
11 years old (n=189)	41.61	40.30	40.00	5.50	4.43
12 years old (n=163)	32.3	35.82	34.29	6.99	5.08
13 years old (n=48)	10.56	4.48	9.52	6.35	4.74
Gender					
Girl (n=289)	54.66	47.76	75.21	6.13	4.60
Boy (n=185)	45.34	52.54	24.79	6.29	4.80

Table 11 presents summary statistics for the sampled children in the present study. A higher proportion of girls were overweight compared to boys but a higher percentage of boys were obese. Also, a considerably higher percentage of girls than boys reported visiting a food outlet during the week of the field data collection. Table 12- Table 16 (inclusive) present summary statistics of food outlet measures broken down by gender (1=male), overweight (1=yes, 0=no), obese (1=yes, 0=no), and reported visit to food outlet (1=yes, 0=no), and separately by geographic container. Also included are the p-values for the Mann‑Whitney U tests for the significant differences across subgroups (or lack thereof).

For the case of unhealthy food outlets (count of convenience and fast-food outlets), Table 12 shows that females encounter over twice the number of outlets in their α-hull activity space, which again, mirrors accurately the actual extent and location of children's local neighbourhood, as delineated by their GPS tracks.

The mean value of unhealthy food outlets changes considerably between the normal weight, overweight and obese groups, according to the container chosen. For the activity space and small buffer containers, for instance, the mean appears lower for the obese group relative to the other two, whereas the opposite trend is observed for the large buffers, although all but two differences among weight categories are not statistically significant. Looking at differences between the obese and overweight group relative to the normal weight, only the 400 m and 800 m network buffer show significant associations that overall retain consistency across the different food outlets.

With regards to differences between the group reporting visiting a food outlet over the course of the data collection week, overall means are as expected, higher for those who reported going versus children that did not. For this outcome, activity spaces and again the 400 m and 800 m network buffers consistently show statistically significant differences among the two subgroups. However, contrary to activity space and Euclidean buffer measures, the two smaller network buffers show higher number of food outlets for children that did not report visiting food outlets, while the two larger network buffers show the opposite. Children that visited a food outlet have moderate to considerably higher number of unhealthy food outlets depending on the container chosen, with up to 23 outlets according to the α-hull containers, 49 according to the SDE and network buffer containers, and over a 100 outlets according to the Euclidean container.

It is worth noting that girls have a considerable higher number of unhealthy food outlets compared to boys, something that is consistent across all geographic containers, but mean differences were not statistically significant.

Table 12. Summary Statistics of Food Environment differences by Gender, Weight Status and Reported Visit to Food Outlet, According to Geographic Container and Outlet Type.

Unhealthy	FEMALE (n = 269)				MALE (n = 185)					Normal Weight (n = 318)				obese (n = 69)					Overweight (n = 156)					Visit Outlet: No (n = 374)				Visit Outlet: Yes (n = 100)				
Food Outlets	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value
Activity Space -Hull																																
α = 10	0.19	0.64	0	4	0.14	0.53	0	4	0.51	0.17	0.60	0	4	0.13	0.57	0	4	0.46	0.13	0.54	0	4	0.29	0.14	0.58	0	4	0.25	0.66	0	4	**0.01**
α = 30	0.44	1.61	0	21	0.31	0.95	0	8	0.78	0.38	1.40	0	21	0.33	1.01	0	4	0.46	0.35	1.13	0	8	0.40	0.29	0.95	0	8	0.68	2.28	0	21	**0.00**
α = 100	0.93	2.50	0	23	0.66	1.53	0	9	0.63	0.83	2.21	0	23	0.59	1.50	0	9	0.53	0.76	2.33	0	22	0.45	0.72	1.90	0	22	1.09	2.77	0	23	**0.03**
Activity Space- SDE																																
1 SD (65%)	0.26	1.76	0	27	0.15	0.70	0	5	0.27	0.22	1.51	0	27	0.19	0.52	0	2	0.13	0.17	0.61	0	5	0.29	0.15	0.64	0	5	0.48	2.81	0	27	0.13
2 SD (95%)	0.94	3.63	0	49	0.85	3.19	0	28	0.80	0.91	3.58	0	49	0.80	2.10	0	12	0.18	0.80	2.34	0	14	0.40	0.80	2.73	0	28	1.25	5.19	0	49	0.72
Euclidean Buffer																																
400m	2.22	4.69	0	61	1.79	2.85	0	15	0.71	1.91	4.09	0	61	1.88	2.53	0	8	0.36	2.05	2.89	0	11	0.47	1.86	2.75	0	15	2.58	6.79	0	61	0.54
800m	8.95	9.95	0	90	8.07	8.22	0	34	0.49	8.11	9.43	0	90	8.67	8.00	0	34	0.54	8.54	8.02	0	37	0.45	8.04	7.77	0	34	9.99	13.04	0	90	0.61
1200m	20.46	17.77	0	126	18.29	15.66	0	115	0.29	18.45	17.67	0	126	20.73	17.18	0	102	0.38	20.30	16.46	0	102	0.29	19.06	15.67	0	115	20.82	21.39	0	126	0.92
1600m	36.91	29.20	0	164	32.51	24.93	0	156	0.30	33.42	29.19	0	164	36.65	27.11	2	149	0.38	36.65	28.45	0	149	0.24	34.87	26.68	0	156	35.30	32.97	0	164	0.50
Network Buffer																																
400m	2.37	5.69	0	36	1.92	4.72	0	28	0.72	1.87	4.72	0	36	3.62	7.39	0	28	0.08	1.74	2.63	0	11	**0.04**	2.53	5.77	0	36	0.59	1.26	0	5	**0.00**
800m	3.85	5.90	0	36	3.41	5.38	0	28	0.46	3.30	5.23	0	36	5.14	7.31	0	28	0.68	7.04	7.64	0	37	**0.02**	3.94	6.03	0	36	2.19	3.31	0	13	**0.02**
1200m	5.46	6.06	0	28	5.61	6.57	0	29	0.95	5.32	6.23	0	29	5.90	6.10	0	23	0.60	17.48	13.87	0	60	0.20	5.31	6.05	0	29	5.73	6.79	0	25	0.85
1600m	10.22	9.56	0	49	9.92	9.69	0	39	0.94	9.67	9.68	0	49	11.28	8.92	0	28	0.97	31.88	24.34	0	129	0.09	9.81	9.24	0	39	10.26	10.81	0	49	0.96

Table 13. Summary Statistics of Food Environment differences by Gender, Weight Status and Reported Visit to Food Outlet, According to Geographic Container and Outlet Type.

Convenience	FEMALE (n = 269)				MALE (n = 185)					Normal Weight (n = 318)				obese (n = 69)					Overweight (n = 156)					Visit Outlet: No (n = 374)				Visit Outlet: Yes (n = 100)				
Stores	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value
Activity Space -Hull																																
α = 10	0.10	0.33	0	2	0.07	0.30	0	2	0.34	0.09	0.31	0	2	0.07	0.31	0	2	0.75	0.07	0.28	0	2	0.56	0.07	0.30	0	2	0.13	0.37	0	2	**0.05**
α = 30	0.16	0.45	0	3	0.15	0.45	0	3	0.97	0.15	0.44	0	3	0.16	0.47	0	2	0.90	0.16	0.49	0	3	0.95	0.13	0.41	0	3	0.24	0.55	0	2	**0.03**
α = 100	0.34	0.76	0	3	0.29	0.71	0	4	0.54	0.32	0.74	0	3	0.29	0.71	0	4	0.71	0.28	0.69	0	4	0.46	0.29	0.72	0	3	0.38	0.79	0	4	0.13
Activity Space- SDE																																
1 SD (65%)	0.36	1.04	0	8	0.39	1.42	0	14	0.53	0.36	1.21	0	14	0.46	1.12	0	6	0.10	0.38	1.01	0	6	0.37	0.37	1.24	0	14	0.40	1.04	0	5	0.75
2 SD (95%)	0.09	0.36	0	3	0.06	0.28	0	2	0.60	0.08	0.34	0	3	0.12	0.32	0	1	0.04	0.08	0.28	0	1	0.30	0.07	0.32	0	3	0.12	0.38	0	2	0.12
Euclidean Buffer																																
400m	0.88	1.33	0	7	0.76	1.21	0	6	0.24	0.75	1.24	0	7	0.86	1.15	0	4	0.27	0.90	1.34	0	6	0.41	0.81	1.21	0	6	0.84	1.49	0	7	0.44
800m	3.26	3.13	0	16	2.85	3.00	0	12	0.61	2.93	3.10	0	16	3.18	2.86	0	12	0.51	3.03	2.97	0	12	0.87	2.98	2.91	0	12	3.34	3.52	0	16	0.60
1200m	7.09	5.18	0	30	6.42	5.23	0	19	0.17	6.42	5.29	0	30	7.06	5.15	0	17	0.41	6.81	5.22	0	22	0.83	6.67	5.05	0	22	7.02	5.64	0	30	0.81
1600m	12.34	8.40	0	39	11.28	8.25	0	37	0.26	11.22	8.61	0	39	12.03	7.93	0	33	0.73	11.80	8.26	0	38	0.97	11.81	8.24	0	38	11.62	8.72	0	39	0.73
Network Buffer																																
400m	1.00	2.39	0	19	0.76	1.83	0	11	0.64	0.80	2.04	0	19	1.32	2.64	0	11	0.03	1.15	2.59	0	19	**0.06**	1.03	2.36	0	19	0.26	0.63	0	3	**0.00**
800m	1.57	2.48	0	19	1.29	2.07	0	11	0.34	1.35	2.22	0	19	1.84	2.63	0	11	0.12	1.68	2.64	0	19	**0.07**	1.57	2.46	0	19	0.85	1.31	0	5	**0.01**
1200m	2.20	2.37	0	13	2.16	2.53	0	10	0.73	2.11	2.45	0	13	2.30	2.13	0	8	0.19	2.26	2.49	0	13	0.47	2.13	2.39	0	13	2.16	2.50	0	12	0.89
1600m	3.98	3.75	0	19	3.79	3.94	0	17	0.60	3.81	3.91	0	19	4.03	3.23	0	11	0.24	3.88	3.67	0	19	**0.58**	3.78	3.72	0	19	4.06	4.16	0	19	0.71

Table 14. Summary Statistics of Food Environment differences by Gender, Weight Status and Reported Visit to Food Outlet, According to Geographic Container and Outlet Type.

Fast Food	FEMALE (n = 269)				MALE (n = 185)					Normal Weight (n = 318)				obese (n = 69)					Overweight (n = 156)					Visit Outlet: No (n = 374)				Visit Outlet: Yes (n = 100)				
Outlets	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value
Activity Space -Hull																																
α = 10	0.09	0.41	0	3	0.06	0.32	0	2	0.46	0.08	0.38	0	3	0.06	0.29	0	2	0.42	0.06	0.33	0	3	0.33	0.07	0.37	0	3	0.12	0.38	0	2	**0.02**
α = 30	0.28	1.42	0	21	0.16	0.58	0	5	0.42	0.23	1.20	0	21	0.17	0.59	0	3	0.51	0.19	0.73	0	5	0.30	0.17	0.62	0	5	0.44	2.15	0	21	**0.02**
α = 100	0.59	2.06	0	22	0.38	0.95	0	5	0.68	0.52	1.77	0	22	0.30	0.85	0	5	0.27	0.49	1.88	0	20	0.43	0.43	1.41	0	20	0.71	2.38	0	22	0.06
Activity Space- SDE																																
1 SD (65%)	0.58	2.95	0	44	0.46	1.86	0	16	0.70	0.55	2.69	0	44	0.33	1.04	0	6	0.74	0.42	1.43	0	10	0.78	0.43	1.63	0	16	0.85	4.49	0	44	0.48
2 SD (95%)	0.17	1.57	0	25	0.09	0.47	0	4	0.47	0.15	1.32	0	25	0.07	0.31	0	2	0.70	0.09	0.45	0	4	0.93	0.08	0.40	0	4	0.36	2.55	0	25	0.38
Euclidean Buffer																																
400m	1.34	3.79	0	54	1.03	1.88	0	11	0.56	1.16	3.24	0	54	1.02	1.56	0	5	0.63	1.15	1.82	0	8	0.27	1.80	0.00	11		5.72	0.00	54		0.81
800m	5.69	7.39	0	78	5.21	5.78	0	27	0.69	5.18	6.86	0	78	5.48	5.77	0	27	0.94	5.51	5.58	0	27	0.30	5.06	5.30	0	27	6.65	10.23	0	78	0.71
1200m	13.38	13.47	0	101	11.87	11.27	0	98	0.44	12.03	13.22	0	101	13.67	13.24	0	87	0.46	13.50	12.38	0	87	0.15	12.39	11.48	0	98	13.80	16.64	0	101	0.95
1600m	24.58	21.92	0	127	21.23	17.54	0	125	0.33	22.20	21.57	0	127	24.62	20.69	2	121	0.25	24.85	21.64	0	121	0.10	23.05	19.57	0	125	23.67	25.16	0	127	0.45
Network Buffer																																
400m	1.38	3.39	0	22	1.17	3.15	0	25	0.65	1.07	2.78	0	22	2.30	5.04	0	25	0.21	1.72	4.01	0	25	**0.04**	1.50	3.57	0	25	0.33	0.85	0	4	**0.00**
800m	2.29	3.62	0	22	2.12	3.64	0	25	0.45	1.96	3.21	0	22	3.30	5.08	0	25	0.18	2.79	4.20	0	25	**0.00**	2.37	3.83	0	25	1.34	2.20	0	9	**0.03**
1200m	3.26	4.09	0	23	3.45	4.37	0	20	0.70	3.21	4.12	0	23	3.59	4.43	0	20	0.72	3.65	4.42	0	20	0.16	3.18	3.97	0	19	3.57	4.85	0	23	0.94
1600m	6.24	6.44	0	39	6.13	6.36	0	25	0.98	5.86	6.33	0	39	7.25	6.55	0	25	0.10	6.92	6.91	0	39	**0.041**	6.03	6.08	0	25	6.20	7.38	0	39	0.83

Table 15. Summary Statistics of Food Environment differences by Gender, Weight Status and Reported Visit to Food Outlet, According to Geographic Container and Outlet Type.

	FEMALE (n = 269)				MALE (n = 185)					Normal Weight (n = 318)				obese (n = 69)					Overweight (n = 156)					Visit Outlet: No (n = 374)				Visit Outlet: Yes (n = 100)				
Supermarkets	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	p-value	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	p-value
Activity Space -Hull																																
α = 10	0.01	0.12	0	1	0.00	0.00	0	0	0.11	0.01	0.10	0	1	0.00	0.00	0	0	0.43	0.01	0.08	0	1	0.74	0.01	0.07	0	1	0.02	0.14	0	1	0.16
α = 30	0.03	0.16	0	1	0.01	0.10	0	1	0.30	0.02	0.14	0	1	0.01	0.12	0	1	0.24	0.02	0.14	0	1	0.98	0.01	0.10	0	1	0.05	0.22	0	1	**0.01**
α = 100	0.04	0.22	0	2	0.02	0.15	0	1	0.41	0.03	0.20	0	2	0.01	0.12	0	1	0.14	0.03	0.18	0	1	0.83	0.02	0.15	0	1	0.06	0.28	0	2	0.17
Activity Space- SDE																																
1 SD (65%)	0.04	0.23	0	2	0.05	0.32	0	3	0.98	0.04	0.28	0	3	0.01	0.12	0	1	0.54	0.05	0.27	0	2	0.31	0.04	0.28	0	3	0.03	0.17	0	1	0.88
2 SD (95%)	0.01	0.09	0	1	0.02	0.16	0	2	0.40	0.01	0.13	0	2	0.00	0.00	0	0	0.43	0.01	0.11	0	1	0.47	0.01	0.13	0	2	0.01	0.10	0	1	0.85
Euclidean Buffer																																
400m	0.10	0.30	0	1	0.14	0.39	0	2	0.40	0.11	0.33	0	2	0.12	0.33	0	1	0.45	0.12	0.33	0	1	0.50	0.34	0.00	2		0.30	0.00	1		0.90
800m	0.41	0.59	0	2	0.44	0.66	0	2	0.73	0.40	0.60	0	2	0.44	0.59	0	2	0.53	0.46	0.63	0	2	0.27	0.42	0.61	0	2	0.40	0.62	0	2	0.66
1200m	1.01	0.94	0	4	1.08	0.97	0	4	0.38	0.96	0.93	0	4	1.05	1.01	0	3	0.84	1.07	0.96	0	3	0.45	1.03	0.93	0	4	1.01	1.02	0	4	0.62
1600m	1.79	1.34	0	6	1.91	1.36	0	6	0.26	1.69	1.36	0	6	1.91	1.38	0	6	0.51	1.85	1.25	0	6	0.41	1.86	1.38	0	6	1.68	1.20	0	5	0.29
Network Buffer																																
400m	0.15	0.51	0	3	0.12	0.40	0	2	0.93	0.11	0.43	0	3	0.25	0.60	0	2	**0.01**	0.17	0.50	0	2	0.12	0.16	0.51	0	3	0.03	0.17	0	1	**0.01**
800m	0.23	0.56	0	3	0.23	0.51	0	2	0.57	0.20	0.51	0	3	0.36	0.64	0	2	**0.01**	0.26	0.55	0	2	0.22	0.24	0.56	0	3	0.17	0.38	0	1	0.61
1200m	0.33	0.59	0	3	0.38	0.65	0	2	0.36	0.34	0.59	0	3	0.38	0.67	0	2	0.99	0.40	0.65	0	2	0.20	0.33	0.60	0	3	0.39	0.62	0	2	0.27
1600m	0.64	0.85	0	3	0.65	0.86	0	4	0.69	0.61	0.84	0	4	0.75	0.86	0	2	0.13	0.69	0.85	0	3	0.19	0.64	0.85	0	4	0.60	0.83	0	3	0.72

Table 16. Summary Statistics of Food Environment differences by Gender, Weight Status and Reported Visit to Food Outlet, According to Geographic Container and Outlet Type.

	FEMALE (n = 269)				MALE (n = 185)					Normal Weight (n = 318)				obese (n = 69)					Overweight (n = 156)					Visit Outlet: No (n = 374)				Visit Outlet: Yes (n = 100)				
Restaurant	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**p-value**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**p-value**	**Mean**	**S.D.**	**Min**	**Max**	**p-value**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**p-value**
Activity Space -Hull																																
α = 10	0.04	0.19	0	1	0.03	0.23	0	2	0.43	0.03	0.21	0	2	0.03	0.17	0	1	0.92	0.04	0.26	0	2	0.80	0.03	0.19	0	2	0.06	0.24	0	1	**0.04**
α = 30	0.11	0.56	0	7	0.05	0.31	0	3	0.24	0.07	0.44	0	7	0.16	0.56	0	3	0.28	0.11	0.43	0	3	0.22	0.06	0.30	0	3	0.18	0.82	0	7	0.16
α = 100	0.30	1.27	0	14	0.14	0.48	0	4	0.36	0.23	1.07	0	14	0.20	0.53	0	2	0.51	0.31	1.26	0	14	**0.05**	0.19	0.87	0	14	0.38	1.41	0	12	0.22
Activity Space- SDE																																
1 SD (65%)	0.28	1.41	0	21	0.32	1.95	0	17	**0.02**	0.30	1.70	0	21	0.28	1.06	0	8	0.51	0.31	1.08	0	8	0.06	0.26	1.44	0	17	0.40	2.18	0	21	0.76
2 SD (95%)	0.08	0.65	0	10	0.06	0.49	0	6	0.33	0.07	0.61	0	10	0.09	0.37	0	2	0.12	0.07	0.32	0	2	0.09	0.04	0.36	0	6	0.18	1.05	0	10	**0.01**
Euclidean Buffer																																
400m	0.77	2.41	0	33	0.43	0.94	0	6	0.21	0.64	2.06	0	33	0.45	0.83	0	3	0.89	0.63	1.18	0	6	0.17	0.53	1.13	0	7	1.00	3.63	0	33	0.73
800m	2.85	5.00	0	59	2.49	3.63	0	30	0.37	2.64	4.67	0	59	2.65	3.08	0	11	0.79	2.70	3.16	0	14	0.39	2.48	3.22	0	30	3.52	7.45	0	59	0.77
1200m	6.91	10.25	0	88	5.75	7.79	0	76	0.17	6.17	9.66	0	88	7.17	9.23	0	65	0.19	7.11	8.91	0	65	0.14	6.07	7.70	0	76	7.81	13.75	0	88	0.81
1600m	13.06	17.14	0	108	10.93	12.16	0	95	0.52	11.83	15.85	0	108	12.94	14.63	0	89	0.22	13.38	16.15	0	89	0.16	11.72	13.67	0	95	14.01	20.37	0	108	0.81
Network Buffer																																
400m	0.67	1.85	0	17	0.46	1.29	0	8	0.55	0.51	1.57	0	17	0.87	1.81	0	8	**0.03**	0.83	1.99	0	17	**0.00**	0.68	1.78	0	17	0.15	0.44	0	2	**0.01**
800m	1.11	2.00	0	17	0.85	1.56	0	8	0.16	0.93	1.79	0	17	1.26	1.87	0	8	0.13	1.28	2.15	0	17	**0.01**	1.07	1.96	0	17	0.60	0.95	0	4	0.17
1200m	1.67	2.08	0	11	1.45	2.02	0	13	0.36	1.53	2.07	0	13	1.64	1.85	0	7	0.49	1.71	2.17	0	11	0.33	1.51	2.02	0	13	1.70	2.08	0	9	0.44
1600m	3.20	3.96	0	39	2.84	3.25	0	21	0.61	2.93	3.74	0	39	3.30	3.04	0	10	0.15	3.54	4.64	0	39	0.12	2.92	3.21	0	21	3.24	4.95	0	39	0.88

Similar to the other group comparisons, by weight and visit food outlet, there is considerable variation in the maximum number of outlets for girls and boys across food outlet. For instance, girls have between 0 (α-hulls) to 11 (EB 1200m) additional convenience stores and between 1 (α-hulls) to 51 (EB 800 m) additional fast-food outlets relative to boys.

Table 17. Logistic Regression Model by Type of Geographic Container

	AH-10	AH-30	AH-100	EB-SD1	EB-SD2	EB-400	EB-800	EB-1200	NB-400	NB-800	NB-1200
OUTCOME: Visit Food Outlet (1=Yes)											
Convenience Stores	1.25	1.75+	1.16	0.57	0.98	0.89	1.00	1.03	0.87	0.86	0.91
Fast Food Restaurants	1.17	1.03	0.99	1.01	1.14	1.15	1.07+	1.01	1.23	1.05	1.07
Restaurants - Full	1.19	1.23	1.08	6.69**	0.91	1.02	0.98	1.00	0.95	0.94	1.01
Healthy Food Outlet (1=yes)	1.35	0.96	1.02	0.00**	0.36	0.56	0.53*	0.54+	0.15*	1.02	0.93
Age	0.97	0.96	0.97	0.98	0.99	0.97	0.98	0.99	0.97	0.99	0.97
Male (1=Yes)	0.42***	0.41***	0.42***	0.41***	0.40***	0.42***	0.42***	0.42***	0.39***	0.40***	0.40***
Unemploment Rate -Census DA	0.97	0.96	0.97	0.98	0.97	0.98	0.97	0.97	0.99	0.98	0.97
BIC	459.4	454.9	460.3	449.3	457.7	447.5	444.6	448.3	453.6	459.9	459.8
AIC	428	423.5	428.8	417.9	426.3	416.4	413.4	417.2	422.2	428.4	428.4
OUTCOME: Obese (1=yes)											
Convenience Stores	1.07	0.96	0.93	1.90	1.27	0.82	0.98	0.98	0.76	0.82	0.93
Fast Food Restaurants	0.83	0.651*	0.70+	0.53	0.64+	0.97	0.97	1.00	1.10	1.05	1.02
Restaurants - Full	1.21	2.37	1.14	1.51	1.21	0.94	1.01	1.02	1.16	1.06	1.05
Healthy Food Outlet (1=yes)	0.92	1.69	2.44+	0.73	1.83	2.80*	1.40	0.75	0.99	1.49	1.06
Age	0.81	0.81	0.84	0.79	0.81	0.78	0.79	0.81	0.81	0.80	0.81
Male (1=Yes)	1.75+	1.86*	1.75+	1.83+	1.84*	1.60	1.69+	1.70+	1.74+	1.73+	1.76+
Unemploment Rate -Census DA	1.05+	1.06+	1.06+	1.05+	1.05	1.04	1.05	1.06	1.06+	1.06	1.05
BIC	345.4	337.5	339.9	342.2	341.6	332.7	337.4	336.8	344.5	343.5	344.8
AIC	313.9	306.1	308.5	310.8	310.2	301.6	306.3	305.7	313.1	312.1	313.4
OUTCOME: Overweight (1=yes)											
Convenience Stores	0.59	0.95	0.55**	0.95	0.89	0.85	0.90	0.93+	0.70	0.76*	0.84*
Fast Food Restaurants	0.85	0.79	0.92	0.85	0.81	0.98	1.01	1.01	1.10	1.10	1.05
Restaurants - Full	5.75	1.48	1.17	1.22	1.26	1.06	1.00	1.02	1.71+	1.28*	1.07
Healthy Food Outlet (1=yes)	0.41	1.88	3.27**	1.31	2.64+	1.70	1.42	1.11	0.74	0.86	1.36
Age	1.00	1.00	1.02	0.99	0.99	0.97	0.97	0.99	0.98	0.95	0.99
Male (1=Yes)	1.22	1.30	1.29	1.26	1.30	1.28	1.27	1.30	1.27	1.27	1.26
Unemploment Rate -Census DA	1.06**	1.06*	1.08**	1.06*	1.06*	1.06	1.06*	1.06*	1.07**	1.07**	1.06*
BIC	512.9	512.5	503.7	517.1	510.9	500.1	500.1	498.5	510.2	508.9	512.2
AIC	481.4	481.1	472.3	485.7	479.5	468.9	468.9	467.3	478.8	477.5	480.8

Note: + $p<0.1$ * $p< 0.05$ ** $p< 0.01$ *** $p<0.001$.
EB: Euclidean Buffer – NB: Network Buffer– AS-SDE1: Activity Space- 1 SD ellipse – AS-SDE2: Activity Space- 2 SD ellipse –
AS α -hull: Activity Space - α -hull

Table 17 presents the results of the logistic regression model for the binary outcomes of visit food outlet (yes/no), obese (yes/no), and overweight (yes/no), with the count of convenience stores, fast-food restaurants, full service restaurants, and the indicator variable for presence of healthy food outlet as well as controls for age, gender, and neighbourhood-level unemployment rate as a proxy for neighbourhood SES (using Statistics Canada data derived from the 2006 Census at the dissemination area level). Coefficients are presented as odds ratio with their corresponding level of significance (+ = $p<0.1$, * = $p< 0.05$, ** = $p< 0.01$, *** = $p<0.001$).

For the outcome of whether children reported visiting a food outlet over the course of the project (seven days), there seems to be a highly consistent significant effect for the covariate corresponding to gender, with boys having a much lower odds of visiting an outlet compared to girls, above and beyond the contribution of all the food outlets and additional control variables.

Regarding the effect of the various food outlets on the odds of visiting a food outlet, there are mixed effects across containers. For several containers the healthy food outlet indicator variable appear significantly and negatively associated with the odds of visiting a food outlet. Interestingly, the number of full service restaurants is significantly associated with higher odds of visiting an outlet. This could be signaling that restaurants can also be sources of unhealthy foods, despite the common practice to classify these outlets as sources of healthy foods. However, this finding is restricted only to the SDE activity space container. Similarly, convenience stores and fast food outlets appear to be associated with the odds of visiting a food outlet only for two of the containers (α -hull=10 and EB 800), but only with a modest statistical significance.

When we observe the coefficients for the odds of being obese or overweight, once more there are no overall consistent results across containers for any of the food outlets. There is a significant association for both fast food restaurants, but with the opposite expected direction: decrease in the odds, for the α -hulls=30 and α -hulls=100 activity space containers.

Similar results were observed for the full service restaurants, with a modest significant and positive effect on the odds of being overweight, corresponding to the 800 network buffer and all three α -hull containers, while an also significant but negative effect is observed for convenience stores in two of the three α-hull containers and the 800 Euclidean and network buffers. Interestingly, the proxy for SES in the census DA where the child lives shows a somewhat consistent significance and positive effect on the odds of being overweight and less consistent for the odds of being obese. Also, it is worth noting that the gender variable appears to significantly increase the odds of being obese but not overweight, again, independent of the contributions of the remaining covariates.

When we observe the coefficients for the odds of being obese or overweight, again there are not overall consistent results across containers for any of the food outlets. There is a significant association for both fast food restaurants, but with the opposite expected direction: decrease in the odds, for the α-hulls=30, α-hulls=100 and SDE2 activity space containers. A similar significant association with the opposite expected direction is observed for the presence of healthy outlets only for the EB 400 container and borderline significant for the α-hull=100. Turning the attention to the results for the binary outcome overweight, similar significant trends with the opposite expected directions are found for convenience stores (α-hulls=100, EB 1200, NB 800 and NB1200) and presence of healthy indicators (α-hulls=100, SDE2 activity spaces). Restaurants, however, appear significantly associated with higher odds of being overweight for two of the three network buffers, something that was not observed for the obese binary outcome. Similarly, convenience stores show statistical significant associations with lower odds of being overweight for four different containers.

Using two residential based (network buffers and Euclidean buffers) and two ego-centric based containers (standard deviational ellipses and α-hulls), an overall consistent association between any of the four food outlet measures and three different health or dietary outcomes for the sampled children could not be identified. However, there seems to be moderate but somewhat consistent evidence of a link between the odds of visiting a food outlet and the food environment around children. Gender and SES differences were also consistently observed regardless of choice of food outlet measure container.

Chapter Seven: Discussion

7.1. Introduction

The literature on environment and health has reached agreement about the existence of *place effects* that significantly shape individual outcomes, above and beyond the contribution of genetic and other individual level factors. And yet, the empirical evidence about the environmental pathways to individual health is inconsistent at best; how or why place matters remains a black box of sorts.

Neighbourhoods, or local environments, are increasingly recognized as playing an important role in overcoming such inconsistencies. Specifically, for children's obesity, the food environment is deemed as a possible mechanism underlying population-level increases in childhood obesity. However, it is less clear what is the most appropriate definition and measurement of this local neighbourhood, and this elusive quest has been appropriately labelled "the holy grail" of urban studies (Spielman & Yoo, 2009). But despite the numerous food environment studies to date, systematic reviews of the literature point to a lack of consistency across studies, with a great heterogeneity in the definition and scope of local food environments, as well as their corresponding food outlet measures (Romain, Casey et al., 2011).

The present study contributes to this body of research through a methodological comparison of current methods for defining children's food environment, and their application to health and dietary behaviour outcomes for a sample of 11-14 year old children. To our knowledge, this is one of the few food environment studies to compare and test a wide range of buffers to define children's local environment. Previous and relevant studies do also include multiple types of containers and activity spaces focused on adults or seniors, or include small sample sizes (Boruff et al., 2012b; Thornton & Kavanagh, 2012; Zenk,Shannon N et al., 2011).

7.2. Highlight of the Analysis

7.2.1. Regarding the Geographic Containers

The analysis presented in the previous chapters focused on evaluating to what extent geographic containers used in the literature represent children's actual use of their local environments. The analysis included containers reflecting a residential-based definition of the neighbourhood, as well as containers derived from ego-centric definitions of the neighbourhood. Network and Euclidean buffers with four distance bands address the former approach, while activity spaces based on standard deviational ellipses (SDE) and α-hull polygons using GPS points address the latter approach.

Since the number of studies using GPS data to analyze children's food environment is still very small, emphasis was placed on comparing the Euclidean, network and SDE containers against the three α-hull containers.

The results of the analysis indicate that the percent of shared area between the various containers and the α-hulls were modest to small, with twenty-five percent of overlapping at best. This weak alignment is even more pronounced when comparing activity space containers and residentially-based buffer containers, and demonstrates that research equating residential neighbourhood with activity spaces, i.e., the areas used and navigated by children, may be based on inaccurate assumptions. These results are consistent with past research comparing Euclidean and network buffers (Apparicio et al., 2008).

In addition, map overlays of 11 of the 13 geographic containers for the same participant (i.e., all but the 1600 m Euclidean and network buffers for ease of visualization) clearly illustrate that overall, activity spaces can not only be much smaller than the residentially-based containers, but also extend outside the boundaries of the residential network buffers, in some cases even outside the 400 m buffers. Furthermore, results of Kappa tests for agreement in food environment measures across the various containers indicate low levels of agreement between each of the food outlet count measures using activity space containers and those obtained using residential-based buffers. Consequently, we can safely assume that differences in the spatial extent and orientation of the geographic container used to define a child's local environment leads to differences in food environment measures.

Among the residentially-based buffers, the 400 m Euclidean buffer displayed the highest agreement with all the activity space containers. This finding is unexpected to some degree, as network buffers are assumed to better mimic individual's use of space by incorporating the street network of their local neighbourhood. However, this might be related to the fact that we are only considering non-motorized movement whereby children use shortcuts through buildings and parks.

7.2.2. Regarding the Influence of the Food Environment on Children's Outcomes

Consistent with the results of the studies reviewed in Chapter 2, results from independent logistic regressions of the food environment by geographic container did not support a consistent effect of the counts of food outlets on either the odds of being obese, the odds of being overweight, or the odds of visiting a food outlet (1=Yes) (Zenk,Shannon N et al., 2011). Still, the 400 m network buffer, and to a lesser extent the 800 m network buffer, showed the highest number of significant effects for all three outcomes. The α-hull containers also displayed statistically significant associations with the odds of visiting an outlet during the seven day data collection period for all food outlet types, above and beyond the effect of the other covariates and the controls for age, gender and neighbourhood level SES. Lastly, there is only empirical evidence of significant lower odds of visiting an outlet for boys, and moderately significant higher odds of being overweight (but not obese) for lower neighborhood SES. Also, when looking at the AIC values between the logistic regression models for each of the containers, they indicate Euclidean buffer containers lead to a smaller information loss than the other models. However, regardless of better model fit parameters, Euclidean buffers departed notoriously from the actual natural spaces that the sampled children used, and among residentially-based containers, only the smaller network buffer containers were closer to the GPS-derived α-hull.

7.3. What is the Best Way to Define Children's Local Food Environments?

After an extensive analysis of thirteen different geographic containers and four different definitions of the local environment for each of the participants, network and Euclidean buffers, SDE and α-hull activity spaces, a logical concluding consideration relates to what is the optimal geographic container to capture children's exposure to the local food environment. The following paragraphs seek to discuss such consideration.

It is evident that ego-centric geographic containers and particularly GPS derived activity spaces do a better job at capturing the areas of the neighbourhood that children actually used relative to either Euclidean or network buffers. These containers are not bound to pre-defined areas or restricted to a given distance from home, school or any other discrete location. Such flexibility may be especially advantageous when studying children, since the variations in size, direction and shape of their actual local environment depend not only on their preferences and time conflicts, but also on those of their parents or caregivers.

However, this superior fit of activity spaces to represent children's local environments does not automatically imply they should be the default definition to analyze the effect of food environment on children's outcomes. The fit of the container directly relates to whether the focus is on food environment as "opportunities" or food environment as "affordances".

7.3.1. Food environment as Opportunities

Food environment as opportunities refer to what can be found in children's local neighbourhood, without presumption of interaction or perception. The focus is therefore on accessibility to healthy or unhealthy foods, and the underlying assumption is that the more accessible potential sources of food are, the more likely are children to perceive them and use them. Residentially based buffer containers can therefore prove useful to capture the effect of accessibility on children's outcomes by including all outlets within a reasonable distance band that can be potentially, if sporadically, used by them.

For instance, network buffers may not actually reflect accurately the exposure to unhealthy food sources. However, they may still offer insight into what food sources could be eventually used, particularly so for network buffers that offer the possibility of analyzing “oriented neighbourhoods with their shape distorted in the direction of, e.g., the closest major road, shops, or transportation station” (Chaix et al., 2009). Results presented in the previous chapters do show better fit for the various children’s outcomes and larger percentages of shared areas relative to Euclidean buffers.

7.3.2. Food Environment as Affordances

Kyttä’s work on ecological perceptual psychology, derived from Gibson’s theory of affordances, provides a framework to analyze this environment-child dynamic. The key of this dynamic, according to their conceptual contributions, lies not on the physical properties of the place, but on their functional properties, whether such place *affords* something to the child (Kyttä, 2004).

Affordance might, therefore, encourage children to engage in activities, from observing what is around them, to actively using what is part of this local environment, but as Storli and Hagen pointed out “action reveals new affordances, and the perception of new affordances creates new action” (2010).

Food environments, more specifically, *afford* different opportunities for children to eat, to buy, to learn about available foods through marketing, and simple visual exploration of food outlets.

The literature distinguishes between potential affordances, or those that are intrinsic properties of the environment and actualized affordances, or those that are first perceived either to be used or to be modified (Kyttä, 2004). While potential affordances can be infinite, actualized affordances are limited to those perceived by the individual. Areas of true exposure can therefore be equated to people’s use of and movement across space and time (Kwan, 2009). It is the notion of actualized affordances that closely reflects the notion of environmental exposure.

Food environment as affordance, thus, rests on the assumption that children's exposure is tied to interaction or perception at the very least, and presumes the extent of their food environment to be restricted to the spaces they actually used. If we consider that the salient characteristic of environmental exposure is the location and duration of children's activity in the environment of interest, in this case the food environment, then the geographic container that capture this child-environment interaction represents "the relevant context of exposure"(Kwan, 2009).

Consequently, food environment exposure cannot be measured by residential based geographic containers, since they include places that children may never come into contact with. The α -hull, on the other hand, is a more accurate representation of children's use of space, and since exposure relates directly to the notion of affordances, that is what children use or at minimum perceive, then α-hulls are more suitable geographic container to measure exposure to the food environment. This can also apply to activity spaces derived from standard deviational ellipses, but the extent and boundaries of the SDE are highly influenced by the spatial deviation of the underlying GPS tracks.

7.4. Limitations

While the present study has sought to contribute to the literature on children's food environment by providing detailed, comprehensive and objective GPS data for a large number of participants, several limitations need to be acknowledged. The present study is based on a week-long period of data collection. Although longer than many previous studies, this might still be a source of spurious associations between the geographic container and the outcomes. It is very possible that children visit more or less food outlets during the specific week of data collection than they would normally, or that the GPS movement used to derive their activity spaces might not represent their typical week. Previous studies have identified limitations regarding accurate representation of children's neighbourhood when using buffers or administrative areas, but we do not anticipate this constitutes a problem for the α -hull containers, or even the SDE containers, since we are taking advantage of GPS technology to derive the activity space geographic containers. In addition, although previous studies have identified limitations due to issues in GPS classification, the focus of our analysis did not require deriving individual trips making this issue less of a concern. However, issues of edge effects might influence the food environment measures in all the residential-based containers and the SDE activity space container, whereby food outlets located immediately outside of the polygon edge can be excluded from the analysis but may be part of the actual food environment for a particular child.

In addition, self-reported diaries were the source of the outcome variable "visit food outlet", and as it is the case with self-reported data, information can be subject to different type of bias (e.g., recall errors) and this might underlie the lack of consistent results in our regression model. We tried to minimize this impact by scheduling daily meetings with the participating children in the project's protocol, to avoid recollection bias and missing data due to lack of understanding of a question or low level of motivation.

Similarly, the present study focused primarily on providing a comparative analysis of the various geographic containers used in the literature, and as such the data collection did not include advertising, signage or other "attractors" for children around the food outlet, or within-store data on the quality, quantity, or price of food items. Future studies should include measures of the local food environment (e.g., what is around children) and measures of the consumer food environment (e.g., what is inside the outlets) (Gustafson et al., 2012).

In addition, as it is the case with previous food environment studies, we did not include information on the home or school environment, and it is possible that children's eating behaviours and weight are likely to be influenced not only by their local neighbourhood food environment, but also by the home and school food environments. Future work should explore how the interaction between these domains affects children's outcomes. Furthermore, by focussing solely on food environments, this study is only considering one half of the energy imbalance equation (i.e., energy intake) which leads one to become overweight or obese. Future analyses of 'obesogenic environments' should also use the methods developed here to consider environments that support or hinder physical activity, or energy expenditure among different populations.

Future work should also extend the analysis presented here to other geographical contexts to allow testing the reliability and validity of the derived food environment measures and the results.

7.5. Concluding Remarks

There is a pressing need to decipher the black box of environmental effects on children's health-related outcomes, and to that effect, this study has focused specifically on the food environments. The main challenge facing studies of children and their built environment lies in how to correctly define what constitutes children's local environment and how this environment might influence their behaviour and their health. In other words, children's use of space dictates not only what are the boundaries of their local environment, but it also defines the frequency of interaction and the consistency of these boundaries. Moreover, children's use of space can differ according to their (and their parents') mobility constraints, age, gender, perception of factors such as safety, convenience, or weather, as well as preferences for time and place of activities.

When assessing the role of local food environment on children's outcomes, studies should select the appropriate geographic container definition depending on whether the focus is on opportunities (accessibility) or affordances (exposure). Accessibility studies may benefit from the use of residentially-based geographic containers, and the associated low cost and relative ease of implementation relative to those associated with GPS data collection. On the other hand, studies focusing on exposure should derive food environment measures only through activity-based geographic containers. Exposure can only be defined in terms of the actualized affordances in local food environments, rather than on potential food opportunity structures that children may or may not encounter in their daily routines, especially given the extrinsic constraints on their mobility (e.g., they are too young to drive, they have limited financial resources for alternative transportation, they often experience parental rules about their movement). Public health professionals, school board officials, and the general public become increasingly aware of the impact that local food environments can have on the growing problem of childhood obesity. If they are to make effective environmental interventions to help curb the childhood obesity epidemic, it will become more important for planners and policymakers to understand and use more accurate methods for identifying the opportunities and affordances for (un)healthy eating in children's everyday environments.

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Appendix A. Systematic Literature Review of GIS based studies of the Food Environment

Reference	year	Population	N	Setting	Measure	Size	Outcome	Container: Network Buffer/distance	Container: Network Euclidean/ distance	Container: Activity Space	Container: Adm. Unit	Food Outlet: KDE	Food Outlet: GRID	Food Outlet:Densit y-Count	Food Outlet:distanc e/Time	Food Outlet: presence /absence	Food Outlet: Index	Food Outlet: Linear Shelf Space	Food Outlet: Clustering
Fraser & Edwards	2010	Children (3-14y)	33594	UK, Leeds	Density/ Proximity	various/closest	BMI				X			X					
Schafft et al.	2009	school districts	92	US, Pennsylvania	Food desert vs. non desert school district (>50% zipcode pop have/don't have grocery (High /Low accessibility of zip code)	10 miles	School % oveweight		X							X			
Lamichhane, et al.	2012	Diabetic youth	845	US, South Carolina	Proximity a-b/Count a-b/Density a&b	na/ a: 2mi urban 6mi rural, b: 1 mi/ 1 & 6 mi bandwidth	BMI	X	X					X					
Epstein et al.	2012	Children (8-12y)	191	US, New York	travel time	0.5 mi	BMI: weigth loss treatment	X							X				
Liu et al.	2006	Children(4-18y)	7334	US, Marion County	proximity to nearest	varies	BMI	X											
Rosenshein and Waters	2009	school - individual data for 5th graders	1149	US, Los Angeles	average distance from centroid of census block groups in school zone to nearest supermarket	varies	percent overweight in school zone				X				X				
Smoyer-Tomic et al.	2008	Neighborhoods	215	CA, Edmonton	pop-weighted mean count	800m/500m	Neigbhorhood SES	X						X					
Fraser et al.	2012	Adults-Women	1198	UK, Bradford	proximity /count/ density/ % obese in cluster	500m-1000m/various/ 250m-500m-1000m	BMI		X		X			X					1

Reference	year	Population	N	Setting	Measure	Size	Outcome	Container: Network Buffer/distance	Container: Network Euclidean/ distance	Container: Activity Space	Container: Adm. Unit	Food Outlet: KDE	Food Outlet: GRID	Food Outlet:Density-Count	Food Outlet:distance/Time	Food Outlet: presence /absence	Food Outlet: Index	Food Outlet: Linear Shelf Space	Food Outlet: Clustering
Thornton et al	2012	adults	1041	UK, Glaskow	proximity\count\density	nearest\0.4 to 5 mi\various	self-reported fruit-veg consumption	X	X			X		X					
Seliske et al.	2012	Children(13-16y)	6971	Canada - excep NB & PEI	Count	500, 750,1000,1500 ,2000	Lunchtime eating outside	X						X					
Ollberding, Nicholas J	2012	adults	American, 33% non-Hispanic white, 31 % other/mixed race).	Hawaii, USA	proximity	0.5 and 3.5 km	food and veg intake		X										
Leete, L	2012	census track	243	portland, Oregon	distance proximity	b) 1 km	food deserts-access				X				X				
Yamashita, Takashi et al	2012	census block	736	Hamilton, Ohio	distance proximity and travel time	distance to closest	accesibility to hf or Unhealthy food				X				X				
Kerr, J et al	2012	atlanta residents	4800	atlanta, georgia	travel time to food outlets (type of food outlet), walking biking driving	1 km	choice of food outlet/ choice of transportation.	X							X				
Saelens et al	2012	childre 6-11y	730	king county, Seattle and San Diego, California	high nutrition (have supermarket and low ffood)/ low nutrition (no supermarket many ffood) index	varies/0.5 miles around block	weight status				X						X		
wall , mm et al	2012	adolescents	2682	minneapolis / st. paul. Minnesota	distances to the nearest supermarket, convenience store, any restaurant, and fast-food restaurant;	1 mile	bmi		X					X	X				
Salois	2012	county-level low income children 2-4y	2192	US	density	varies	obesity				X			X					
Dubowitz, t et al	2012	women 50-79y	60775	national study -WHI CT-	counts per 1000 persons	.75 -1.5 - and 3.0 miles	DBP, obesity (1-0) hypertension(1-0)		X					X					

Reference	year	Population	N	Setting	Measure	Size	Outcome	Container: Network Buffer/distance	Container: Network Euclidean/ distance	Container: Activity Space	Container: Adm. Unit	Food Outlet: KDE	Food Outlet: GRID	Food Outlet:Density-Count	Food Outlet:distance/Time	Food Outlet: presence /absence	Food Outlet: Index	Food Outlet: Linear Shelf Space	Food Outlet: Clustering
Hurvitz, Phillip et al	2012	students, staff and faculty U. Washington	41	seattle, US	count in cell	30 BY 30	environment differences between home and						X	X					
An & Sturm	2012	children and adolescent	8226 children (5-11years) 5236(12-17years)	california	count	0.1 0.5 1.0 and 1.5 miles	Food Consumption-FFQ/BMI		X					X					
shaw, hillary	2012	birmingham population	285 MLSOA	birmingham , UK	proximity-ecludian distance from residential grid	grid 250 x250 meters	percent obesity - percent eating FFV						X		X				
shaw, hillary	2012	INSEE statistical area -residential only-	189	nantes, france	proximity-ecludian distance from residential grid	grid 250 x250 meters	percent obesity - percent eating FFV						X		X				
block, jason et al	2011	adults	3113	massachussets framingham	proximity to food store - walkability model	number of intersections per mile	time-varying individual BMI		X										
gordon, larsen et al	2011	adolescents	11088	Longitudinal Study of Adolescent Health (Add Health), a	proximity to food outlet	3 km from participant home	number of fast food meals in a week -obesity	X											
carr, Lucas et al	2011	adults	379	rhode island	walkability proximity	1 mile	reliability walk schore		X										
ford, paula et al	2011	low income mothers	21166	kansas	presence	census track	BMI									X			
Russell, Scott et al	2011	block gorup	not specified	new haven, Connecticut	proximity	1-4 mile, 1-2 mile, 1 mile from food outlet	food deserts-access	X											
Eckert, jeanette et al	2011	birmingham population	not specified	toledo, Ohio	distance to closest food outlet	varies	food deserts-access	X							X				
Svastisalee, chalida et al	2011	Neighborhoods	400	copenhagen	count	varies	availability of Food outlets				X			X					
Howard	2011	chiildren- 9th grade	879	California-all schools	proximity(yes/no)	800m	school overweight rate	X											

Reference	year	Population	N	Setting	Measure	Size	Outcome	Container: Network Buffer/distance	Container: Network Euclidean/ distance	Container: Activity Space	Container: Adm. Unit	Food Outlet: KDE	Food Outlet: GRID	Food Outlet:Density-Count	Food Outlet:distance/Time	Food Outlet: presence /absence	Food Outlet: Index	Food Outlet: Linear Shelf Space	Food Outlet: Clustering
Villanueva	2012	children(10-12y)	926	Australia	Count	800m /min convex hull		X		X				X					
brennan and carpenter	2009	children and adolescent	529367	California	proximity/count	0.25, 0.5, 0.75m	bmi, fast food comsumption		X					X					
harris et al	2011	adolescents	552	maine	proximity/count	2 km	bmi	X						X					
Austin et al	2005	schools	1351	chicago	proximity/count/clustering	na/400 800/na	clustering around schools		X			X		X					1
Hulst et al	2012	children(8-10y)	512	Montreal, Quebec City and Sherbrooke, QC	proximity/density from school + home	na/1 km	fruit- Veg and sugar drink intake	X				X		X					
Casey et al.	2012	children(10-12y)	3293	France	proximity AND distance	1000 m	weight		X						X				
Leung et al.	2011	girls(6-7y) at baseline	353	San Francisco Bay Area, US	count/ density	0.25 mi, 1 mi	weight gain over 3 years	X						X					
Mercille et al	2012	seniors(68-84y)	751	Montreal	proportion FFO/all rest- proportion healthy stores/all food stores - index	500m	dietary patterns	X									X		
Shier and Sturm	2012	children (5th and 8th graders)	6260	US -from national study	1) counts per 1000 pop/ 2) index / 3) Indicator (0-1)	varies	BMI/BMI change from 5th to 8th grade				X			X			X		
Hill et al	2012	US census block groups	39	Danville, VA	count	varies	racial/income differences				X			X					
sanchez et al	2012	children -5th, 7th, 9th grades-	926018	California	counts/density	0.5 mi	overweight/obesity		X					X					

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richardson et al	2012	young adults (18-28y)	13995	US - NATIONAL SAMPLE - Add Health	count per 100km of roadway	participant home (also comparative analysis with 1	food resource availability	X	X					X					
Lee et al	2012	children(5-10y)	7730	US -National Sample - ECLS-K	count/ outlets per density/ outlets per sq mi/ percent of each outlet type out of all outlets -percent shares- BOTH at baseline and growth/changes over study time	varies	BMI changes				X			X					
boone-heionmen et al	2011	adults(18-30y)	5115	US-National study - CARDIA	count per 100000 pop	1, 1-2.99, 3-4.99, 5-8.05 KM	consumpion, diet quality fruit and veg recommende		X					X					
kestens, et al	2012	18y>	5578	Canada - Montreal - National study -CCHS	foodstore kernel density	varies	overweight			X	X			X					
Moore et al	2008	adults(45-84 years)		Carolina, USA. Baltimore, Maryland.	density	1,6km	dietary pattern							X					
Chaix et al	2012	(30-79 years)	7132000	paris, France	presence-distance-s	5000 m radius	BMI		X						X	X			
Mercille et al	2012	census track	248	Montreal, Canada	aereal density	varies	absolute availability- relative availability				X			X					
He - Gilliland	2012	children 11- 13 years	810 (21 elementary schools)	london, Ontario	density- proximity	1 km	food purshasing	X						X					
He - Gilliland	2012	children 11- 13 years	810 (21 elementary schools)	london, Ontario	distance_ counts	1km	Food Consumption-FFQ	X						X	X				
Rossen et al	2013	children 8 - 13years old	319 children	Baltimore City	counts food outlets, HFAI	100- 800 meter	BMI gain	X						X			X		
Rose et al	2009	adults	1243 person	lousiana, USA	cumulative linear shelf space of fruits, Vegs and snack foods	100-500-1000-2000 meters	BMI	X										X	

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bodor et al	2008	adults	102 person	new orleans, Lousiana.	distance to small stores and supermarkets/presence of small store and supermarket/linear shelf space within buffer for veg/fruits	meters (1000 for presence of supermarket)	fruit- Veg intake		X						X	X		X	
zenk et al	2011	adults	131	detroit, Michigan	density FF- presence S	0.5 for Network Buffer		X		X				X		X			
Nelson et al	2010	Adults 18-23 years	48	minnesota	distance-presence	1/2, 1 , 2 miles	eating and food purchasing behaviours	X							X	X			
Lebel et al	2012	adults	29 Montreal, 36 Quebec	island, quebec city, Canada	density ff and restaurants		BMI overweight/obesity			X	X			X					
fietchner et al	2012	age 2 - 6.9 years old	438 children	Massachussets, Usa	proximity to food outlets	≤1 mile,>1 to2 miles and>2 miles.	BMI	X											
kestens et al	2010	>4y	individuals in Montreal and 68,121 in Quebec City	Montreal and Quebec City	residence exposure- activity space exposure. KDE	varies	exposure							X					
Galvez et al	2009	6-8 years old	323 boys and girls	East Harlem, New York	count	varies	BMI				X			X					
Thornton and Kavanagh	2012	adults	2547	Melbourne, Australia	weighted density	2km	fast food purchasing		X					X					
Hirsch	2013	adults	50	Philadelphia	distance	varies	shopping behaviours, perception of Fe		X						X				
Seliske et al.	2009	children grade 6-10	7281	Canada - HSBC national sample	presence of each FO type around schools/food retailer index/ density per pop in buffer	1 km 5 km	overweight		X					X		X	X		
Heroux et al	2012	13–15 years old	26,778 students from 687 schools	Canada, Scotland and the US.	presence of each FO type around schools in buffer	1 km	eating at FO during school time. overweight		X							X			

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Ellaway et al	2012	schools	29	glasgow	Ratio of observed to expected K density	400, 800, 1200, 1500 meters	clustering around schools		X					X					1
Goldsberry	2010	residential addresses	94 retail locations	Lansing, Michigan, USA	presence/count/ distance	0,1 - 0,2 miles/ 10 min walk	approach cartographic outputs can be	X						X	X	X			
bodor et al	2010	adults	3925 adults	new orleans, Lousiana.	count/distance	2km census track	BMI		X										
Forsyth et al	2012	adolescents	adolescents at 20 secondary schools	minneapolis / st. paul. Minnesota	counts/distance to nearest	800m 1600m/varies	frecuency eating at Fast Food restaurant	X						X	X				
Fraser et al	2012	13y longitudinal at 15y	4827	Avon region, UK	distance-weighted density	1000 m	BMI/fast food consumption	X						X	X				
Morland & Evenson	2008	Adults	1295	Forsyth, NC and Jackson, MS	median count (>=1/< =0) for FO with higher freq, presence for FO with small frequencies /distance nearest superm-ffood	varies	obesity	X			X			X	X	X			
Hutchinson et al	2012	adults	1243	lousiana, USA	ratio of linear shelf space for healthy and junk foods/ food storedensity	500m, 1km 2km	overweight	X						X				X	
Zick et al	2009	adults 25y-64y	453927 -UPDB population database	Lake County, Utah	dummies for presence of eath type, multiple types and no food outlet	varies	BMI				X					X			
Day & Pearce	2011	schools		New Zealand	count-proportion/ K- clustering	400m-800m/1.5 km	clustering around schools	X	X					X					1
christian	2012	adults 18-85y	101	Lexington, KY	count per type/ RFEI/ ffood-supermarket density and proportion	varies	food consumption-survey/weigth status			X	X			X					
Jenning	2011	children 9-10y	1669	Norfolk, UK	count PER km2/ presence of one or multiple FO types	800 m	BMI/food intake	X						X		X			
Cerin et al	2011	adults 18-65y	274	atlanta, georgia	counts -intensity-/distance to nearest/ number of types of FO -diversity-	1 km	weight status	X						X	X				
Truong et al	2010	adults >18	43020	California - CHIS survey	PFEI	varies	BMI				X						X		
black and Day	2012	schools	1392	british columbia, canada	count	800 m	availability of Food outlets												

VITA

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EDUCATION

PhD. Human and Community Development, University of Illinois at Urbana-Champaign, 2012
M.S. Human and Community Development, University of Illinois at Urbana-Champaign, 2006
M.Sc. Department of Geography, University of Western Ontario, 2013
B.A. Education, San Buenaventura University, Cartagena, Colombia, 2004

PUBLICATIONS

- Gilliland, J., Rangel, C., Healy, M., Tucker, P., Loebach, J., Hess, P., He, M, Irwin, J., 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), S15-S20.

- Rangel, C., and Lleras, C. (2010) Educational Inequality in Colombia: Family Background, School Quality and Student Achievement in Cartagena. *International Studies in Sociology of Education*, 20(4), 291-317.

- Lleras, C. and Rangel, C. (2009). Ability Grouping Practices in Elementary School and African American/Hispanic Achievement. *American Journal of Education*, 115, 279-304.

RESEARCH EXPERIENCE

Research Associate.
University of Western Ontario.
Human Environment Analysis Laboratory –HEAL-.

- Search, collect, compile and prepare databases for statistical analysis.
- Perform Statistical Analysis using appropriate software (Stata, SPSS)
- Spatial analysis of data using ArcGIS and other spatial analysis software.
- Collaborate in the writing process of the research project, as well as in the preparation of tables and graphs to present the research findings.
- Field work across schools in the region that take part in the STEAM -Spatio-temporal Exposure and Activity Monitoring- project looking at environmental influences on children's health issues, particularly obesity/Physical Activity. Daily follow-up with children, preparation of equipment, qualitative surveys, training session for participant schools.

Research Associate.
University of Western Ontario.
Welcoming Communities Initiatives. University of Western Ontario and Immigration Canada.

- Secondary data analysis and compilation of baseline indicators as part of the WCI -Welcoming Communities Initiative- using Canadian census data and national datasets on immigrant health.
- Data collection and analysis of restricted-use CCHS –Canadian Community Health Survey- for statistical analysis.
- Data collection and analysis of restricted-use EQAO data for all schools in Ontario.

TEACHING EXPERIENCE

Lecturer/Instructor
Fanshawe College, London, ON.

- METH7003: Databases for GIS – Integrated Land Planning Technologies Program
- METH1001: Databases for GIS – GIS and Urban Planning Program

Teaching Assistant.
University of Western Ontario, London, ON

- Geography of Canada – Department of Geography
- Latin America and the Caribbean – Department of Geography
- GEOG 3211: Spatial Statistics – Department of Geography
- GEOG 1100: Fundamentals of Geography – Department of Geography
- G3222B: Geographic Information Science II – Department of Geography