DELINEATING NEIGHBOURHOOD AND EXPOSURE IN BUILT ENVIRONMENT AND PHYSICAL ACTIVITY RESEARCH

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Suzanne Mavoa

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ABSTRACT

Several decades worth of public health research has shown that characteristics of people's environment are associated with health-related behaviours and outcomes. Much of this research has used the concept of a residential neighbourhood to delineate the relevant environment. However, there is no uniformity in the neighbourhood delineation methods used in the literature and little consideration is given to whether they adequately capture people's exposure to the environmental characteristics under investigation, or whether the choice of delineation methods influences results. This dissertation has addressed these issues and suggested some methods researchers may use to delineate spatial context more precisely.

The first part of the thesis used data from a study of neighbourhood environment and physical activity in adults to examine the impact of different methodological choices on modelling results. Both neighbourhood delineation method and scale were shown to determine whether significant associations were found between the built environment and physical activity. Modelling results also varied depending on the built environment and outcome measures used. A detailed exploration of different methods of operationalising the road network buffer demonstrated that, even for a single neighbourhood delineation method, methodological choices can alter the results.

The second part of the thesis used GPS data from a study of children's physical activity and independent mobility to examine how well a number of road network buffers and activity space delineation methods represented exposure to the environment. Results showed less than half of children's seven-day activity was captured by residential road network buffers at a range of scales. Most activity space delineations were better representations of where children spent time than road network buffers. However, the measures of activity space commonly used in health research - the convex hull and standard deviation ellipse – were poor representations of exposure.

Activity space delineations require detailed location data that is not always available. Therefore, there is a need for delineation methods that do not require this data. Five enhancements to standard road network buffers were proposed. One enhancement - including school and home in the buffer - was tested and shown to be an improvement on standard road network buffers.

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ABBREVIATIONS

BMI	Body Mass Index
CATI	Computer-Aided Telephone Interview
CAU	Census Area Unit
CBD	Central Business District
CCD	Census Collection District
CVD	Cardiovascular Disease
DA	Dissemination Area
DPA	Daily Path Area
dph	Dwellings per hectare
ED	Enumeration District
GIS	Geographic Information Systems
GPS	Global Positioning System
Ha	Hectare
IPEN	International Physical Activity and Environment Network
KDE	Kernel Density Estimation
KITC	Kids In The City
km	Kilometres
m	Metres

MAUP	Modifiable Areal Unit Problem
MB	Meshblock
mi	Mile
MVPA	Moderate-Vigorous Physical Activity
NA	Not Applicable
NDAI	Neighbourhood Destination Accessibility Index
NO2	Nitrogen Dioxide
RNB	Road Network Buffer
s	Seconds
SD	Standard Deviation
SDE	Standard Deviation Ellipse
SES	Socio-Economic Status
UGCoP	Uncertain Geographic Context Problem
UK	United Kingdom
URBAN	Understanding the Relationship Between physical Activity and Neighbourhood

Chapter 1. Introduction

Over the past three decades, public health researchers have generated a significant body of literature examining the associations between environment and health. Much of this literature has conceptualised the environment as a residential neighbourhood and then gone on to examine whether variations in environmental attributes at the neighbourhood level predict differences in the health-related behaviours or outcomes. In doing so, residential neighbourhood boundaries have come to be used as proxies for exposure to the environment.

There are two problems with this approach. First, a number of methods – such as census areas and circular buffers – have been used to delineate the residential neighbourhood boundary. However, while there is evidence that the choice of delineation method and the size of the neighbourhood boundary can change research results (James et al. 2014, Parenteau and Sawada 2011, Prins et al. 2014, Colabianchi et al. 2014, Veugelers, Kim and Guernsey 2000), it is not clear which of the many delineation methods and scales are optimal.

The second, more important, problem lies in the conflation between the core concepts of 'neighbourhood' and 'exposure.' Although these concepts are often used interchangeably, they have different meanings. Neighbourhood denotes an area in the vicinity of something; for instance, a residential neighbourhood refers to the area near home. Exposure, on the other hand, refers to the external influences an individual is subjected to in a particular location.

Clearly, as a number of researchers have noted, the residential neighbourhood does not usually represent an individual's total exposure to the environment (Matthews

2008, Chaix et al. 2009, Cummins et al. 2007). Conversely, there are likely to be a number of locations within a residential neighbourhood that individuals rarely visit, and so little or no exposure occurs. Ultimately, individuals may be exposed to locations beyond a residential ‘neighbourhood’ and may not be exposed to locations within that neighbourhood. This distinction between the potential exposure of a neighbourhood and actual exposure is not always explicitly acknowledged, yet it is an important consideration when interpreting research results, and selecting and developing appropriate delineation methods.

Together, these issues suggest that public health researchers’ interest in assessing exposure to the environment is outpacing the development of appropriate methods to delineate both the residential neighbourhood and exposure to the broader environment. Furthermore, they indicate a need to pay attention to the definition of place related concepts (Matthews and Yang 2013) and critically consider the operationalisation of these concepts to ensure that we are measuring what we think we are measuring.

1.1 Dissertation goals and aims

This dissertation addresses the challenge of delineating boundaries in environment and health research by: 1) exploring how different methodological decisions in delineating the residential neighbourhood influence research findings; 2) determining how well the current best practice method of delineating the residential neighbourhood captures the places people travel and spend time; and 3) exploring and proposing new delineation methods that better capture potential and actual exposure to the environment.

While this work is relevant to the wider neighbourhoods and health literature, the data used in the analyses come from studies of the relationship between the built environment and physical activity in New Zealand adults and children. The built environment and physical activity literature is substantial and, due to the work around increasing sedentary behaviour and rising obesity rates, it is one of the main areas in which health researchers are investigating the issue of boundary delineation.

PhD Goals:

1) Provide evidence to assist in appropriate selection and delineation of boundaries in environment and health research.
2) Propose new/improved methods of delineating boundaries that better represent actual and potential exposure to the environment.

PhD Rationale:

Contribute to more robust measurement of the neighbourhood – and, therefore, the environment - individuals are exposed to.

PhD Aims and Research Questions:

1) Review existing delineation methods and the effect of these on built environment and health research results.
2) Explore the influence of analysis choices on residential neighbourhood delineation and relationships between the built environment and physical activity in New Zealand adults.
    a. How do different delineation methods and scale choices change research results?
    b. How does the choice of outcome measure interact with different delineation methods to change research results?
    c. Does the choice of buffering algorithm change the size of the boundary and resulting measures of the built environment?
3) Determine how well road network buffers – the current best practice method of delineating residential boundaries - represent actual exposure to the environment.

4) Determine whether different activity spaces improve on road network buffers as a method of delineating exposure to the environment.
5) Propose, develop, and test enhanced road network buffer delineations to capture exposure to the environment.

1.2 Thesis Structure

Chapter Two reviews existing methods of delineating boundaries, summarises the literature investigating the effect of different neighbourhood definitions on study results, reviews approaches for identifying the optimal neighbourhood boundaries, and discusses theoretical issues that arise when delineating boundaries.

Chapter Three addresses the second aim of the thesis, which is to explore the influence of methodological choices on residential neighbourhood delineation and relationships between the built environment and physical activity in New Zealand adults. The three research questions comprising this aim are addressed in this chapter using data from the Understanding the Relationship between Physical Activity and Neighbourhood (URBAN) study; an investigation of the association between built environment and physical activity in New Zealand adults.

Chapter Four describes relevant methods and data from the Kids in the City (KITC) study; a study of the relationship between the built environment and New Zealand children's independent mobility and physical activity. Demographic, Geographic Information Systems (GIS), and Global Positioning System (GPS) data from this study are used in the analyses presented in Chapters Six, Seven, and Eight.

Chapter Five provides detailed methods and descriptive analyses related to GPS inclusion/exclusion criteria. This is an essential step in ensuring that the GPS data used in subsequent chapters is as robust as possible.

Chapter Six addresses the third aim of the thesis. GIS analysis is used to calculate the overlap between road network buffers (potential residential exposure) and actual exposure as measured by seven-day GPS data. Limitations of road network buffers are identified.

Chapter Seven addresses the fourth aim of the thesis. GIS analysis is used to calculate the overlap between different methods of delineating activity spaces and actual exposure as measured by seven-day GPS data.

Chapter Eight draws on the limitations of road network buffers to propose five enhancements that may allow road network buffers to represent actual and potential exposure around both residential addresses and general life spaces more accurately. One enhancement – the inclusion of school in the buffer delineation – is tested with the KITC data and compared to standard road network buffers. Potential methods of implementing the other four enhancements are described.

Finally, **Chapter Nine** links the dissertation in a discussion and conclusion.

Appendix A is a detailed statement of candidate contributions to the two research studies used in this thesis. **Appendices B-C** contain supplementary descriptive statistics and modelling results.

1.3 General statement of candidate contributions

This doctoral dissertation uses data from two studies of the built environment and physical activity conducted in New Zealand: the URBAN study, and the Kids in the City study. The candidate was an investigator and a member of the research team on both studies. Candidate contributions to each study are summarised in the relevant chapters with additional detail provided in Appendix A.

A part of the research undertaken for this dissertation has been submitted as a journal article and is currently under review:

Mavoa, S., Bagheri, N., Koohsari, M.J., Kaczynski, A.T., Lamb, K.E., O'Sullivan D., Witten, K. (under review). The influence of different neighbourhood definitions on the relationship between the built environment and physical activity.

The candidate conceived the idea for the manuscript in collaboration with dissertation supervisors (Witten and O'Sullivan), conducted all GIS and statistical analyses, and wrote the first draft of the manuscript. Co-authors contributed to the development of the research idea, the choice of statistical methods, interpretation of results, and editing the manuscript. Bagheri and Lamb provided advice on the statistical methods and interpretation of model results. The research in this manuscript is a major component of Chapter 3, Sections 3.1-3.3. The analysis and interpretation of the different physical activity outcome measures and all other sections of Chapter 3 – namely the analysis of different algorithms (Section 3.4), and the commentary on methodological issues arising from these analyses (Section 3.5), are solely the candidates work.

Chapter 2. Literature review: Delineating neighbourhood and exposure

2.1 Introduction

An essential step in any research investigating relationships between the environment and health is conceptualising and operationalising/delineating the spatial extent of the area of interest (Diez Roux 2001). This chapter reviews the public health literature on the delineation of neighbourhood and exposure to the environment, and - where appropriate - draws on relevant research from other fields.

The next two sections explore the related concepts of 'neighbourhood' and 'exposure', defining the use of these terms within this thesis. The following sections review existing methods of delineating boundaries, investigate whether different neighbourhood definitions and delineations make a difference to results, review approaches for identifying the optimal neighbourhood boundaries, and identify and discuss theoretical issues that arise when delineating boundaries. The final section summarises the chapter.

2.2 Neighbourhood

A focus of research on the built environment and health has been whether neighbourhood influences health, independent of an individual's characteristics (Diez Roux 2007). While neighbourhood is a fundamental concept, it is rarely defined explicitly and there is no clear, single definition of what it means (Hipp, Faris and Boessen 2012, Stein 2014, Ross, Tremblay and Graham 2004, Stafford, Duke-Williams and Shelton 2008). The Oxford English Dictionary gives a variety of definitions of neighbourhood, ranging from the purely spatial - “a district or portion of a town, city, or country” or “the vicinity or surrounding area” - to those that include people, for instance, “the people living near to a certain place or within a certain range; neighbours collectively” or “a community” (Oxford English Dictionary).

These definitions reflect the fact that neighbourhoods can be both spatial and social spaces (Lupton 2003). As such, neighbourhoods can be conceptualised as spatial or socio-spatial units (Guo and Bhat 2007, Sawicki and Flynn 1996).

Researchers’ definitions of neighbourhood have reflected this spatial versus socio-spatial distinction. For example, Lebel et al. (2007), define neighbourhood as “a place characterized by a specific collection of spatially-based features that can be found at a specific geographic scale.” Whereas for Chaskin (1995), neighbourhood is a “geographically bound unit in which the residents share proximity and the circumstances within that proximity” (p. 1).

While consideration of neighbourhoods as socio-spatial units is important - and starting to receive attention in broader neighbourhoods research (Hipp et al. 2012, Hipp and Boessen 2013) - within health research, neighbourhoods are most commonly viewed as purely spatial units (Dietz 2002, Guo and Bhat 2007, Macintyre, Ellaway and Cummins 2002, Spielman and Yoo 2009). Perhaps one of the most complete definitions of neighbourhood as a spatial feature is Galster’s (2001), in which a neighbourhood is “the bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses” (p. 2112). For the remainder of the dissertation neighbourhoods are considered as spatial units only.

In the literature, ‘neighbourhood’ often appears to refer to a number of concepts related to place, such as ‘context’, ‘place’, ‘neighbourhood’, ‘neighbourhood environment’, ‘local area’, ‘small area’, and ‘local environment’. These terms are often used interchangeably (Gauvin et al. 2007), despite the fact some are used in reference to the residential neighbourhood alone, whereas others, such as ‘context’ and ‘place’, could refer to locations beyond the residential. Within this dissertation, the term ‘neighbourhood’ will be used to refer to the residential neighbourhood.

2.3 Towards improved conceptualisation of context: From neighbourhood to exposure

Neighbourhoods and health research has primarily focused on residential neighbourhoods. Yet other spatial contexts may have implications for health (Diez Roux 2001). Cummins et al. (2007), have argued that a relational view of place – one that acknowledges people are mobile and allows for dynamic and fluid definitions of area - is essential to improve our understanding of the relationships between place and health. They labelled the problem of focusing solely on the local as the ‘local trap’. Chaix et al. (2009), later refined the concept of the ‘local trap’, coining the phrase ‘residential trap’, to refer to the problem of focusing solely on the residential environment. Given the loosening of our dependency on residential locations (Matthews and Yang 2013), both the local and residential traps are likely to be an increasing problem for researchers aiming to delineate and measure the environment.

These critiques of delineations of context that focus solely on the residential neighbourhood represent a conceptual shift from neighbourhood to exposure. While residential neighbourhoods are still pertinent, researchers are increasingly interested in developing a more nuanced understanding of exposure that goes beyond the residential.

Exposure can be defined as “the state or fact of being subjected, to any external influence” (Oxford English Dictionary). Public health research already has an interest in exposure when the external influences – whether social, or chemical, physical, and biological as in exposure science (Lioy and Smith 2013) - are associated with health behaviours and outcomes.

Since residential neighbourhoods are unlikely to be an adequate proxy for exposure (Madsen et al. 2014), researchers have called for better conceptualisation and measurement of human exposure (Matthews and Yang 2013, Kwan 2012a, Chaix 2009, Cummins et al. 2007). This desire for greater precision in the delineation of context aligns with a general move towards greater specificity in built environment and health research (Giles-Corti et al. 2005).

2.4 Operationalising context

Operationalisation, or delineation, of the spatial extents (i.e., boundaries) of both neighbourhood and exposure is an essential part of environment and health research. However, delineating the spatial extents of both the residential neighbourhood (Ross et al. 2004), and exposure (Cummins et al. 2007) are unresolved and interrelated challenges.

The delineation of boundaries is typically undertaken using GIS software. There are numerous methods that can be used to delineate a spatial extent, and the choice of method can produce boundaries of different sizes and shapes. Furthermore, measuring the environment within these different areas can lead to different research results.

Table 1 presents existing delineation methods and groups them within four categories: territorial; ego-centric; location-centric; and activity space. This categorisation is based on the work of Chaix et al. (2009) - who reviewed theoretical issues relating to the delineation of ego-centric neighbourhoods - and has been extended to capture a broader range of delineation methods used in the literature.

Table 1. Main types of delineation methods.

Type of delineation	Delineation method	Examples
Territorial	Administrative units	Morland et al. (2002) Smith et al. (2008)
	Aggregated administrative units (zones)	Riva et al. (2009) Sabel et al. (2013)
	Buffered administrative units	Frank et al. (2012)
	Environmentally defined areas (natural neighbourhoods)	Cutchin et al. (2011) Stafford et al. (2008) Ross et al. (2004)
Ego-centric	Euclidean buffers	Bell, Wilson and Liu (2008) Lovasi et al. (2009)
	Network buffers	Badland et al. (2009) Frank et al. (2007)
	Participant defined neighbourhoods	Basta, Richmond and Wiebe (2010) Coulton et al. (2001) Smith et al. (2010)
Location-centric	Euclidean buffers	Parks and Schofer (2006)
	Network buffers	Pearce et al. (2008)
Activity space	Convex hull	Shareck, Kestens and Gauvin (2013) Villanueva et al. (2012) Yin et al. (2013)
	Standard deviation ellipse	Hirsch et al. (2014) Kamruzzaman and Hine (2012) Zenk et al. (2011)
	Daily path area	Hirsch et al. (2014) Lipperman-Kreda et al. (2015) Zenk et al. (2011)

The list of delineation methods was obtained from recent theoretical articles and literature reviews that specifically consider the delineation of boundaries (Brownson et al. 2009, Carter and Dubois 2010, Schaefer-McDaniel et al. 2010, Feng et al. 2010, Chaix et al. 2009, Wong, Faulkner and Buliung 2011), and supplemented by journal articles describing empirical studies.

Figure 1 (on the following page) illustrates a few of the different types of delineations for a single residential address with hypothetical GPS data. The delineation methods are discussed in detail below.

2.4.1 Territorial units

Territorial units are mutually exclusive “entities that have a social consistence independent of a specific individual” (Chaix et al. 2009, p. 1306). Administrative and census areas are examples of territorial units. Territorial units have most often been used to represent residential neighbourhoods, but they can be used to represent context beyond the residential (e.g., Wong and Shaw 2011). Four common types of territorial units are described below.

2.4.1.1 Administrative units

Until recently, the majority of health research delineated neighbourhoods used pre-existing administrative units such as meshblocks, census tracts, enumeration districts and suburb boundaries. The use of administrative units to represent where participants live is still popular, presumably because they are predefined, relatively simple to use, and readily available. In addition, and perhaps more importantly, secondary data sources, such as census data, are often defined at an administrative unit level, making it easy to include such data in research (Diez Roux 2007, Pickett and Pearl 2001).

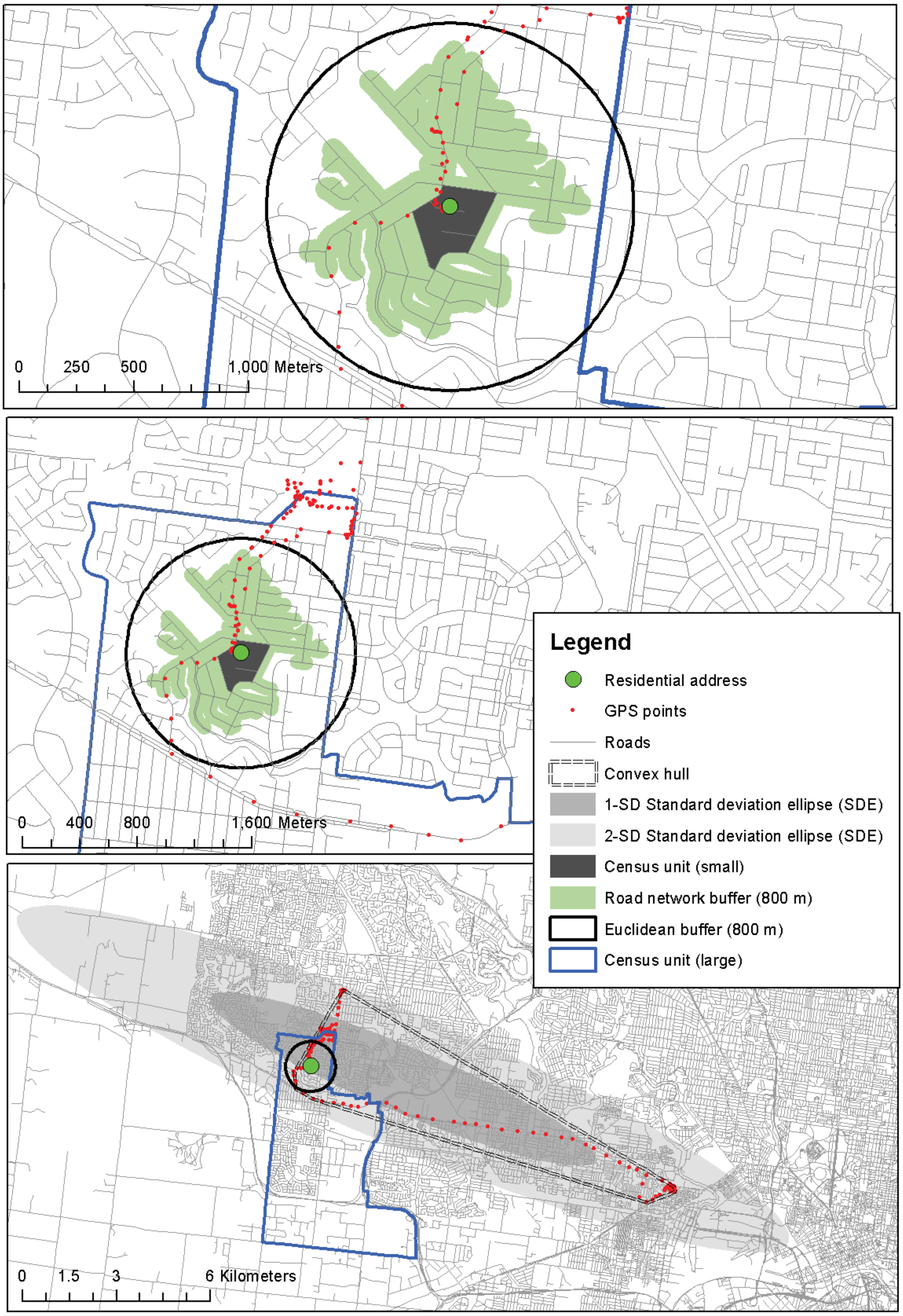


Figure 1. Examples of delineation methods for a theoretical individual.

Examples of empirical studies that used administrative units to delineate the environment include Smith et al. (2008) who measured neighbourhood walkability within census tracts, and Morland et al. (2002) who measured food accessibility within census tracts.

2.4.1.2 Aggregated administrative units (zones)

To delineate boundaries using aggregated administrative units, small administrative units - typically the smallest available census area - are used as building blocks to form larger aggregated administrative units. Relatively few researchers have used aggregated administrative units, perhaps because it requires the additional step of creating new zones, which is not always straightforward.

Automated zone design techniques provide methods of aggregating administrative units. Cockings and Martin (2005), took enumeration districts - the smallest census unit in the UK - and designed a zoning system at different scales and aggregation levels in order to explore the relationship between neighbourhood deprivation and health in a UK county. Riva et al. (2009), designed zones for Montreal based on Canadian dissemination areas. They designed their zones to be homogenous over the exposure variable of 'active living potential'.

While most researchers have used small administrative units as the zone/neighbourhood building blocks, Sabel et al. (2013), recently developed an experimental automated zone design method, using a small tessellated cell as a basic building block, to create new synthetic neighbourhoods in France. They found correlations between asthma and deprivation were higher for their new zones than French census areas of a similar size. As a result, they argued that the careful construction of neighbourhoods can aid our understanding of relationships between the social and physical neighbourhood environment and health.

While some researchers have aggregated units based on homogeneity of a particular characteristic (Riva et al. 2009), others have argued against using homogeneity as a criteria to create zones (Chaix et al. 2009, Pickett and Pearl 2001, Ross et al. 2004). Although homogeneity may be relevant for defining sampling units or implementing interventions, it may not be relevant as the sole criteria with which to delineate areas an individual is exposed to. In other words, a zone/neighbourhood need not be homogenous to affect the lives of residents.

2.4.1.3 Buffered administrative units

The use of buffered administrative units is a response to boundary problems. Boundary problems – also called edge effects – are where study areas such as neighbourhoods are bounded by a discrete border, yet the spatial processes are not (Fotheringham and Rogerson 1993). For instance, if a participant lives on the edge of a neighbourhood, the characteristics of the adjacent neighbourhood may be more relevant than the characteristics of the neighbourhood the participant resides in. Boundary problems are particularly relevant for territorial units. Techniques to address them have long been discussed in geography, but are still new in health research.

Recently, Frank et al. (2012), have used buffered administrative units in a study of the environment and adolescents physical activity. In this study, a census block group buffered by a 0.25 mile radius was used as the residential neighbourhood.

2.4.1.4 Natural neighbourhoods

Some researchers have suggested that neighbourhoods need to be 'natural', or 'ecologically meaningful' (Pickett and Pearl 2001). These terms describe functional neighbourhood units that are delineated to better represent the local-level activity spaces of individuals by ensuring they contain the appropriate composition of physical and social characteristics (Bissonnette et al. 2012).

Researchers have taken different approaches to the delineation of natural neighbourhoods. Some create 'natural' neighbourhoods by aggregating administrative units based on homogeneity of variables (Parenteau and Sawada 2011). Natural neighbourhoods created in this way are the same as aggregated administrative units.

Another approach has been to create natural neighbourhoods by drawing on local knowledge. Ross et al. (2004), for example, have delineated natural neighbourhoods using a combination of housing district maps, historical documents, census data, local perceptions, and consultations with real estate agents. This type of approach may also end up creating neighbourhoods based on aggregated administrative units.

A small number of studies have delineated natural neighbourhoods based on physical features of the environment, such as roads, rivers and areas of parkland (Stafford et al. 2008, Cutchin et al. 2011). Because physical features play an important role in daily life - for example, most people have to travel around a lake - it is likely that physical features are an important component in determining realistic neighbourhood boundaries. As such, a consideration of physical features might have the potential to improve boundary delineation; either alone, or in combination with other methods.

2.4.2 Ego-centric delineations

In contrast to territorial units, ego-centric delineations are individually defined. These types of spatial extents are unique for each individual, although spatial extents for different individuals can overlap (Chaix et al. 2009). Delineating ego-centric boundaries around locations relevant to individuals (e.g., home, workplace) is becoming more common and there are several methods to achieve this.

2.4.2.1 Euclidean buffers

Euclidean buffers – also called ‘straight-line buffers’, or ‘radial buffers’ - are created by drawing a circle centred on a point relevant to an individual participant, with a radius/scale defined by the researcher (Oliver, Schuurman and Hall 2007). Euclidean buffers assume that every part of the circle is as accessible as every other part. In other words, they ignore barriers (e.g., water, private property) and travel routes and paths (Chaix et al. 2009, Oliver et al. 2007). Therefore, Euclidean buffers may not be the most appropriate method of delineating exposure to the environment for certain types of environmental measures (e.g., access to destinations and services) and behaviours (e.g., commuting to work). However, for some kinds of environmental exposures (e.g., air pollution, noise) and for behaviour that is less restricted (e.g., children’s roaming beyond official networks), Euclidean buffers may be appropriate representations of neighbourhood and exposure.

Examples of the use of Euclidean buffers include Bell et al. (2008), who calculated greenness within a 1 km Euclidean buffer around residential addresses, and Lovasi et al. (2009), who used a 1 km Euclidean buffer to represent the residential neighbourhood, in a study that measured neighbourhood walkability.

2.4.2.2 Network buffers

Network buffers are calculated by measuring a distance over a network from a point of interest, with the distance/scale determined by the researcher (Oliver et al. 2007). The most common network used in the creation of network buffers is the road network. Numerous researchers have used road network buffers at a range of scales to represent the residential neighbourhood (e.g., Badland et al. 2009, Frank et al. 2007, Adams et al. 2014, Villanueva et al. 2014, Thornton, Lamb and Ball 2013).

However, the creation of neighbourhoods based solely on road networks assumes that people only travel along roads. In reality, people may also travel along pedestrian paths/tracks or alleyways, as well as through buildings, parks and public open space.

Little research has examined the impact of including or excluding pedestrian paths when creating road network buffers, and none has explicitly examined the impact on network buffer size and shape. The two existing studies that have compared street networks with and without pedestrian paths have demonstrated that excluding pedestrian routes from road network buffers can result in different measures of street connectivity (Chin et al. 2008, Tal and Handy 2012). Therefore, it is likely that the inclusion or exclusion of pedestrian routes in street networks will influence the size and shape of network buffers.

The accuracy of road network buffers is also dependent on the accuracy of the underlying road network data. Research into the accuracy of commercially available road data in the United States has highlighted issues with completeness, currency and accuracy (Zandbergen and Ignizio 2011, Frizzelle et al. 2009). However, unless researchers go through the time-consuming process of creating a customised road network for each study (e.g., Frizzelle et al. 2009), they are reliant on existing road network data. Therefore, it is important to be aware of the impact that the quality of this data can have on network buffers.

Other issues can arise in the calculation of road network buffers. These include the algorithm and software used to calculate the buffer (Forsyth et al. 2012), and whether the distance from a location to the road centreline is taken into account in the buffer calculation.

Despite these issues, in many cases road network buffers represent a conceptual advance on neighbourhoods defined by Euclidean buffers, since network buffers are seen as a better representation of places people can travel to. However, road networks may not be as appropriate as Euclidean buffers when assessing exposure or behaviour that is not limited by roads.

2.4.2.3 Euclidean and network buffers around different locations (home, work, school, and travel routes)

Euclidean and road network buffers have most commonly been calculated around home addresses. To date, very little environment and health research has been conducted around non-residential locations. Inagami et al. (2007), found that including non-residential exposure increased the magnitude and significance of the association between residential neighbourhoods and health and could explain why other studies have not found strong associations between neighbourhoods and health. More recently, Hurvitz and Moudon (2012), found differences between the residential and non-residential neighbourhoods.

Researchers have also started to demonstrate significant differences between home and work environments. Burgoine and Monsivais (2013), found that the food environments around homes and workplaces were very different and that the levels of relative exposure between residential and work and commuting environments were poorly correlated. Others have demonstrated significant associations between the work environment characteristics and health-related outcomes such as cardiovascular disease (CVD) risk (Chum and O' Campo 2013), and usual travel mode to work (Dalton et al. 2013).

Regardless of the type of buffer used, or the non-residential location examined, all these methods are still examples of ego-centric methods, since each location is relevant to an individual. Additionally, these methods - that start to look at delineations around locations other than home - may have some overlap with activity space methods (see Section 2.4.4).

2.4.2.4 Participant defined neighbourhoods

A number of studies have asked participants to delineate their own neighbourhood boundaries (e.g., Basta et al. 2010, Coulton et al. 2001, Smith et al. 2010). Comparison of these perceived neighbourhood boundaries with territorial units has shown they do not match (Robinson and Oreskovic 2013, Colabianchi et al. 2014, Vallée et al. 2015). Furthermore, the degree to which residents agree on neighbourhood boundaries differs across locations (Colabianchi et al. 2014). This suggests that the discrepancy between researcher and resident-defined neighbourhoods is a possible source of bias in neighbourhood effects studies (Coulton et al. 2001). In addition, many researchers have observed variation in the size and shape of participant defined neighbourhood boundaries (Basta et al. 2010, Colabianchi et al. 2014, Coulton et al. 2001, Coulton and Jennings 2013, Vallée et al. 2015), suggesting that individuals living in the same vicinity perceive their neighbourhood differently.

Studies have found that the areas of perceived neighbourhoods differ from the areas of road network buffers (Crawford et al. 2014) and that there is little overlap between perceived neighbourhoods and road network buffers in adults (Smith et al. 2010), adolescents (Colabianchi et al. 2014) and children (Villanueva et al. 2012).

While perceived neighbourhood boundaries are of interest for many research questions, they may not be an appropriate mechanism for delineating areas of exposure to the environment. Indeed, the extent to which perceived and objective neighbourhoods represent actual exposure are unanswered questions. Some of the first work to explore these questions has used GPS data to show that perceived neighbourhood boundaries better captured where youth spent time and were physically active than census tracts (Robinson and Oreskovic 2013).

2.4.3 Location-centric

Location-centric delineations use ego-centric methods, but create buffers around pre-defined locations that do not specifically relate to an individual. For example, Parks and Schofer (2006), defined neighbourhoods by creating circular (i.e., Euclidean) buffers around centres of activity such as concentrations of commercial land.

Network buffers have also been calculated around administrative unit centroids (Pearce et al. 2008, Sharkey and Horel 2008). This approach has some of the benefits of using network buffers, in that it more accurately represents paths that people can move along within their neighbourhood, and partially addresses edge effects. However, the extent to which these location-centric buffers represent the territorial unit will depend on the scale of analysis, and the method used to create administrative unit centroids (e.g., geometric centroids versus population weighted centroids; Thornton, Pearce and Kavanagh 2011).

2.4.4 Activity spaces

An activity space has been defined as "the space within which people move about or travel in the course of their daily activities" (Vallee et al. 2010, p. 838). It includes both the places people visit and the places people travel through but don't visit (Schönfelder and Axhausen 2003).

The places that comprise an activity space can be thought of in the context of Oldenburg's (1989) theorising on third places, community environments that enable social interaction. In this framework, home is conceptualised as an individual's first place, and workplace/school as their second place. Third places can be further categorised as destinations (e.g., parks, shops), thresholds (e.g., driveways, front porches) and transitory spaces (e.g., roads, pathways; Carroll et al., 2015). An activity space encapsulates the first, second and third spaces frequented by an individual and the routes between these destinations.

Activity spaces have a long history in transport, geography and other social sciences. Over the past few years, they have been adopted by health researchers. For example, activity spaces have recently been examined in relation to exposure to food (Kestens et al. 2010), mental health (Vallee et al. 2011), alcohol outlets (Basta et al. 2010) and the built environment (Colabianchi et al. 2014).

As with the delineation of neighbourhoods, there are numerous methods of delineating activity spaces and the choice of method determines both the shape and area of the activity space (Sherman et al. 2005). Just as the activity space concept has been adopted from other fields, so too have many of the activity space delineation methods. This is potentially problematic, since the purpose of delineating activity spaces differs between research fields. For instance, in the transport field, activity spaces are used as a measure of mobility, with the size of the activity space polygon indicating the degree of mobility (Schönfelder and Axhausen 2003).

While some health researchers have used activity spaces to assess mobility (e.g., Hirsch et al. 2014, Villanueva et al. 2012), others have used activity spaces to delineate exposure to the environment. These researchers have measured the characteristics of the environment within the activity space and then modelled associations with various health-related outcomes (e.g., Zenk et al. 2011, Shearer et al. 2015, Lipperman-Kreda et al. 2015, Christian 2012, Crawford et al. 2014, Colabianchi et al. 2014). This approach can be problematic if the activity space delineation contains large areas that participants never visit – as is the case with two of the common activity space methods discussed below – or if they exclude areas participants do visit. For instance, Figure 1 (above) illustrates the potential for this problem to arise when using activity space measures such as convex hulls and standard deviation ellipses (SDE).

The most common methods of delineating activity spaces are discussed below.

2.4.4.1 Standard deviation ellipses

The standard deviation ellipse (SDE) is a bivariate statistical measure that geographically describes areal point data (Yuill 1971). SDEs capture the spatial distribution of points around a mean centre and create an ellipse at one or two standard deviations from this centre. Therefore, a 1-standard deviation ellipse (1-SDE) contains approximately two-thirds of the points (Arcury et al. 2005). An SDE requires points as input and these points can be weighted, for example, by activity duration or frequency (Sherman et al. 2005).

Historically, SDEs have been used to delineate activity spaces (Sherman et al. 2005). Initially, SDE based activity spaces were created around point locations of regular destinations obtained through surveys (Sherman et al. 2005), participatory mapping (Townley, Kloos and Wright 2009) or activity diaries (Kamruzzaman and Hine 2012). However, since the adoption of GPS technology, researchers have increasingly calculated SDEs using GPS data (e.g., Zenk et al. 2011, Hirsch et al. 2014, Madsen et al. 2014) or mobile phone data (e.g., Järv, Ahas and Witlox 2014). Modifications of the SDE have included SDE's created using only GPS points located within the residential neighbourhood (Boruff, Nathan and Nijenstein 2012), and calculating time-weighted SDEs (Crawford et al. 2014).

The main limitation of the SDE is that it is an abstract representation of where people go. As a Euclidean measure, it does not account for actual spatial arrangements of geographic or human features. Furthermore, SDE's typically include large areas that are not visited (Wong and Shaw 2011).There can also be technical challenges – such as an unusual spatial distribution of destinations, or too few visited destinations - that make it difficult to calculate the ellipse (Wong and Shaw 2011). However, the SDE provides a better indicator of individual access than distance alone, and is now relatively easy to generate with available software.

2.4.4.2 Convex hulls

Convex hulls - also called minimum convex polygons - are the smallest convex polygons that enclose a set of points (Galton and Duckham 2006). Therefore, like the SDE, convex hulls require a dataset of points as input. When using convex hulls to delineate activity spaces researchers have used commonly visited destinations (Shareck et al. 2013, Villanueva et al. 2012) and GPS points (Boruff et al. 2012, Shareck et al. 2013, Yin et al. 2013) as input.

The limitations of convex hulls are similar to those of the SDEs. Convex hulls include large areas that people do not visit (Wong and Shaw 2011, Chaix et al. 2012), and with certain numbers or configurations of points they can be difficult to create (e.g., if all destinations are in a straight line).

2.4.4.3 Daily path areas

The daily path area is a method of activity space delineation adapted from Kwan (1998). The daily path area takes GPS points as an input and buffers them to create the activity space. A number of recent studies have delineated activity spaces using daily path areas (e.g., Zenk et al. 2011, Hirsch et al. 2014, Lipperman-Kreda et al. 2015) and the buffer distances used to create the daily path areas have ranged from 50 m (Shearer et al. 2015) to a half mile (i.e., approximately 800 m; Zenk et al. 2011).

2.4.5 Other delineation methods

The methods described above represent the most commonly used delineation methods. However, a small number of methodological studies have proposed the use of alternative methods of delineating both neighbourhood and exposure. In a statistical approach similar to the SDE method, Buliung and Kanaroglou (2006), delineated a standard distance circle around a mean centre, with the radius being the standard distance of activity locations. In an approach based on territorial units, Wong and Shaw (2011), identified visited locations using travel survey data and delineated the activity space by combining all census tracts that contained visited locations. Kestens et al. (2010), also used travel survey data, however they delineated activity spaces using kernel density estimation (KDE).

Boruff et al. (2012), have suggested modifications to the SDE, convex hull and road network buffers, based on the location of common walking trip destinations. Using GPS data, they identified common walking trip destinations within 1 km of the residence and created an SDE and convex hull using only these destinations as input. Their modified road network buffer comprised the shortest network distances from the residence to each destination. They also proposed the use of a variable width buffer based on a raster cost-surface approach commonly used in ecology (Boruff et al. 2012). When testing the alternate buffering methods, they found these techniques provided better model fit when modelling the relationship between land use and walking.

Finally, Madsen et al. (2014), have pointed out that while activity space methods are useful, activity spaces rely on detailed location data (e.g., GPS), which may not always be available. They noted there is still a need to develop better buffers that do not require such data. To address this problem they created two types of buffers oriented towards the central business district (CBD). The first were buffers based on the shortest network distance between home and the CBD, and the second were elliptical buffers oriented between the home and the CBD. While these methods are an important advance they still have limitations. Shortest network distance buffers exclude other potential routes and focus on journeys between destinations rather than activity at destinations. The elliptical buffers suffer from the same limitation as the convex hull and SDE; namely, they can include large areas not visited by participants.

While many of these novel delineation approaches are promising, no other researchers have tested or adopted them to date.

2.5 Does the choice of delineation method affect research results?

Given the numerous delineation methods available, researchers are increasingly testing the impact of their choice of delineation method and scale on research results. Table 2 summarises these findings.

Table 2 has shown the impact of different delineation methods and scales for a range of exposures, outcomes, and population groups. The first thing to note is that there was little consistency in the neighbourhood delineation approaches and scales compared in these studies. For example, some studies only compared territorial units, while others only compared ego-centric methods; some investigated multiple scales, and others used a single scale.

The final column of Table 2 indicates whether the different delineation methods made a difference to results. Again, there was no standard method employed to identify meaningful differences. Therefore, the results in the difference column were based on the conclusions of each individual study.

Almost all the studies in Table 2 concluded that different neighbourhood delineation methods and/or scales made a difference to results. However, there were three exceptions. Ross et al. (2004) concluded that their natural neighbourhoods were 'remarkably similar' to census tracts. Given the very similar estimates produced by the fully adjusted models – 0.98501 (p< 0.01) for the natural neighbourhoods and 0.98578 (p<0.01) for census tracts – their conclusion appears valid. The two models do not appear to be meaningfully different. This similarity could be because the natural neighbourhoods and census tracts were created using the same administrative unit building blocks (i.e., enumeration areas). Furthermore, both the exposure and outcome measures were measured using enumeration areas.

The second study to conclude that neighbourhood delineation methods did not make a difference to results also compared neighbourhoods created using the same building blocks (i.e., enumeration districts; Jones et al. 2010). Again, the use of the same base units may have contributed to the similarity of results for the different delineation methods.

Finally, in a study of associations between walkability and walking in four different age groups at four different scales, Villanueva et al. (2014), concluded there was no difference between different sized road network buffers. Their conclusion was based on results indicating that, for most – but not all - age groups examined, there was some evidence to suggest higher walkability was associated with more walking. However, their results also produced different odds ratios at different scales, and for some population groups the scale of the road network buffer determined whether a significant association was detected. This is an example of the inconsistency in approaches for determining what constitutes a meaningful difference between delineation methods. If the criteria used in some of the other studies were applied, here, this study would have concluded the choice of scale did make a difference to the results.

The studies in Table 2 employed a total of six main approaches to identify whether delineation methods and scales differed. In some cases, more than one of these comparison techniques has been used.

The first, and simplest, approach was a comparison of the areas of spatial extents produced by the different delineation method (e.g., Crawford et al. 2014). Second, some studies examined whether the territorial neighbourhood a participant resides in predicted an outcome (e.g., Riva et al. 2009, Jones et al. 2010). Third, some studies

Table 2. Research comparing the effect of different delineation methods.

Source	Exposure measures	Outcome measures	Population	Delineation methods	Difference
Basta et al. (2010)	Alcohol outlets	-	Male adolescent victims of assault (n = 55)	Participant defined Census unit (census tract)	Yes
Boone-Heinonen et al. (2010)	Built environment	Physical activity	Adolescents aged 11-22 (n = 20,745)	Euclidean buffers (1, 3, 4, 8.05 km)	Yes
Boruff et al. (2012)	Land use	Walking	Retirement village residents (n = 74)	Euclidean buffer (1 km) Road network buffer (1 km line based) Road network buffer (1 km polygon based) RIC line buffer RIC polygon buffer RIC SDE	Yes
Burgoine and Monsivais (2013)	Food environment	-	Working age adults (n = 2,696)	Residential Euclidean buffer (1 mi) Residential network buffer (1 mi) Work Euclidean buffer (1 mi) Work network buffer (1 mi) Commute route (100, 500 m buffer around the shortest route between home and work dependent on mode)	Yes
Christian (2012)	Food environment	Dietary intake Food purchasing Obesity	Adults aged 18-65 residing in a single census tract (n = 121)	Census tract GPS daily path area (0.5 mi radius)	Yes
Veugelers et al. (2000)	Built environment	Active travel	Adults 15 years and over (n = 1,855)	Unspecified buffers (200, 300, 400, 500, 600, 800, 1000, 1600 m). Grids (200, 400, 800, 1600 m). Census units (census tract, dissemination area)	Yes

Cockings and Martin (2005)	Deprivation	Long term illness	Census population (n = NA)	Aggregated census units based on ED Census units (wards)	Yes
Coffee et al. (2013)	Walkability	Cardiometabolic risk	Adults aged 18 years and over (n= 4,041)	Census units (CCD, suburb) Network buffer (500, 1000, 1600 m)	Yes
Colabianchi et al. (2014)	Built environment	Physical activity Overweight Obesity	Urban minority adolescents (n = 125)	Census unit (census tract) Network buffer (0.75 mi) Activity space (convex hull)	Yes
Coulton, Cook and Irwin (2004)	Social indicators	-	Population (n = 7,496)	Census unit (census block) Participant defined	Yes
Crawford et al. (2014)	Food environment	-	Low income women of reproductive age (n = 34)	Participant defined Network buffers (0.5, 1, 1.5, 2 mi) Activity space (1-SDE)	Yes
Duncan et al. (2014)	Tobacco outlets	-	Youth (n = 1,292)	Euclidean buffers (400, 800 m) Network buffers (400, 800 m) Census units (tract, block group)	Yes
Etman et al. (2014)	Built environment	Walking for transport	Older persons aged 65 years and over and residing in the community (n = 408)	Network buffers (400, 800, 1200, 1600 m)	Yes
Flowerdew, Manley and Sabel (2008)	Census	Self-reported health	Census population (n = NA)	Aggregated census units based on ED	Yes
Guo and Bhat (2007)	Census Built environment	Residential location choice	Households (n = 4,791)	Census units (tract, block, block group) Euclidean buffers (0.25, 1, 2 mi) Network buffers (0.25, 1, 2 mi)	Yes
Chaskin (1995)	Built environment	MVPA	Adults aged 21 – 59 (n = 55)	Unspecified buffers (50, 250, 500 m) Grids (100, 500, 1000 m)	Yes
James et al. (2014)	Built environment	Walking BMI	Female nurses aged 25-52 (n = 17,433)	Euclidean buffers (400, 800, 1200, 1600 m) Network buffer s(400, 800, 1200, 1600 m)	Yes
Jones et al. (2010)	Neighbourhood	Physical activity	Children aged 11 years (n= 3,935)	Census unit (ED) Aggregated census units version 1 Aggregated census units version 2 Natural neighbourhood	No

Learnihan et al. (2011)	Walkability	Walking for transport Walking for recreation	Adults moving into new homes (n= 1,811)	Census units (CCD, suburb) Network buffer (15 minute walk at 6.44 km/hr)	Yes
Lipperman-Kreda et al. (2015)	Tobacco outlets	Tobacco use	Adolescents aged 14-18 (n = 11)	Home Euclidean buffer (800 m) School Euclidean buffer (800 m) GPS daily path area (50, 100 m radii)	Yes
Madsen et al. (2014)	-	-	Regular cyclists (n = 78)	SDEs (1-SDE, 2-SDE) Network buffers (1, 2 km) Shortest route buffers (500, 750, 1000 m radii) Ellipse between home and CBD (500, 750, 1000 m radii) Variable buffer	Yes
Messer, Vinikoor-Imler and Laraia (2012)	Physical incivility Walkability Social spaces	Pregnancy related behaviours and outcomes	White and black women who delivered singleton infants (n= not reported)	Census units (census tract, census block group) Natural neighbourhoods (secondary polygons, tertiary neighbourhoods)	Yes
Mitra and Buliung (2012)	Built environment	Active school transport	Children aged 11 – 12 (n = 2,520)	Euclidean buffers (250, 400, 800, 1000 m) Census unit (dissemination area) Traffic analysis zone	Yes
Moore et al. (2013)	SES Social environment, Physical environment	BMI	Workers (n = 1,503)	Residential Euclidean buffer (1 mi) Work Euclidean buffer (1 mi)	Yes
Parenteau and Sawada (2011)	NO2 concentrations	Respiratory disease	Census adults 15 years and over (n= NA)	Census unit (census tract) Aggregated census units Natural neighbourhoods	Yes
Prins et al. (2011)	Built environment	MVPA	Adolescents (n = 277)	Euclidean buffers (400, 800, 2000 m)	Yes
Riva et al. (2009)	Census	Walking	Adults 45 years and over (n = 2,716)	Aggregated census units based on DAs	Yes
Robinson and Oreskovic (2013)	-	MVPA	Adolescents aged 11-14 (n= 32)	Census unit (census tract) Participant defined	Yes
Ross et al. (2004)	Census	Health status	Adults 25-64 (n= 1694)	Natural neighbourhood based on enumeration areas Census unit (census tract)	No

Shearer et al. (2015)	Food environment	Dietary intake	Adolescents aged 12-16 (*n* = 380)	Network buffer (1 km) GPS daily path area (50 m radius)	Yes
Tatalovich et al. (2006)	Census	-	Children (*n* = 5,763)	Census unit (census block) Minimum bounding rectangles	Yes
Thornton et al. (2013)	Food environment	Dietary behaviour	Women aged 18-65 (*n* = 1,555)	Home network buffers (0.8, 2 km) Work network buffers (0.8, 2 km)	Yes
Vallée et al. (2015)	Health resources	-	Adults (*n*= 653)	Euclidean buffer (367 m) Participant defined	Yes
van Loon et al. (2014)	Built environment Social environment	MVPA	Children aged 8 – 11 (*n* = 366)	Network buffers (200, 400, 800, 1600 m)	Yes
Villanueva et al. (2012)	-	-	Children aged 10 – 12 (*n* = 1,480)	Network buffer s (800, 1600m) Activity space (convex hull)	Yes
Villanueva et al. (2014)	Walkability index	Self-reported walking	Adults aged 18-29 (*n* = 1,663), 30-44 (*n* = 2,546), 45-64 (*n* = 4,703), 65 and over (*n* = 3,611)	Network buffers (200, 400, 800, 1600)	No
Zenk et al. (2011)	Built environment	Dietary behaviour Physical activity	(*n*= 121)	Network buffer (0.5 mi) SDE (1-SDE) GPS daily path area (0.5 mi)	Yes

RIC = retail, institutional, and commercial land uses.
ED = Enumeration district (UK).
CD = Census collection district (Australia).
MVPA = Moderate-vigorous physical activity.
SES = Socio-economic status.
NO2 = Nitrogen dioxide.
DA = Dissemination area (Canada).

compared characteristics of the delineated areas (e.g., Christian 2012, Zenk et al. 2011).

The fourth, and increasingly popular, approach was to model associations between the environment measured within the different delineations and health-related outcomes (e.g., Veugelers et al. 2000, Boone-Heinonen et al. 2010, James et al. 2014, Prins et al. 2011, Colabianchi et al. 2014, Jones et al. 2010, Parenteau and Sawada 2011, Ross et al. 2004). These studies varied in how they identified optimal models and delineations. Some studies assessed whether statistical significance was reached (e.g., Colabianchi et al. 2014, Zenk et al. 2011, James et al. 2014); some compared the strength of associations (e.g., Boone-Heinonen et al. 2010, van Loon et al. 2014, James et al. 2014); and others examined model fit statistics (e.g., Parenteau and Sawada 2011).

Fifth, a small number of researchers assessed the extent of the spatial overlap between the areas created by the different delineation methods (e.g., Villanueva et al. 2012, Colabianchi et al. 2014).

Finally, even fewer researchers used GPS data to compare how well delineation methods captured where participants travelled and spent time (e.g., Madsen et al. 2014). This last type of comparison is the only approach that compares delineation methods with actual exposure. While it is informative to explore how different delineation approaches change modelling results, it is perhaps more useful to select delineation methods based on how well they capture exposure. The lack of such evidence is a notable gap in research around delineation methods.

None of the studies in Table 2 offered a definitive conclusion about a single optimal delineation method or scale. Indeed, researchers frequently acknowledged this limitation (Chaskin 1995, Veugelers et al. 2000, Boone-Heinonen et al. 2010, James et al. 2014, Cockings and Martin 2005) and the need for future research to address this issue. Several researchers identified strategies to mitigate this limitation, such as reporting at multiple scales (Boone-Heinonen et al. 2010), and use of zone design techniques (Cockings and Martin 2005, Flowerdew et al. 2008, Riva et al. 2009, Riva et al. 2008, Jones et al. 2010).

2.6 Theoretical considerations

This section describes additional theoretical considerations that are important when delineating neighbourhood and exposure. While some of these considerations are drawn from the list provided by Chaix et al. (2009), additional considerations of scale, time, the Modifiable Areal Unit Problem (MAUP), and the Uncertain Geographic Context Problem (UGCoP) have been added.

2.6.1 Scale

Appropriate choice of scale is important for both territorial and ego-centric delineation methods. For territorial delineation, since the scale of the administrative units used is usually predefined, the choice consists of deciding which sized units are most appropriate. For example, meshblocks versus census area units in New Zealand; census tracts versus census blocks in the United States; and enumeration districts versus census output areas in the United Kingdom.

When creating Euclidean and network buffers, however, the scale or distance is defined by the researcher. While scales used to delineate buffers range from 100 m to 8050 m (Brownson et al. 2009), they are most commonly based on rules of thumb (e.g., 400 m 800 m, and 1600 m). These distances are commonly cited as the distance people can walk within 5, 10 and 20 minutes, respectively (Yang and Diez-Roux

2012, Austin et al. 2005). The 1600 m distance also represents the distance a person walks in 15 minutes at the speed suggested by the U.S. Surgeon General as being required to achieve ‘moderate’ intensity physical activity (Giles-Corti et al. 2005).

Despite their apparent foundation in common-sense, these distances may not adequately represent actual distances people travel. Evidence from household travel surveys conducted in Brisbane, Australia and the US suggests that walking distances to destinations were greater than the distances typically used when generating buffers (Burke and Brown 2007, Yang and Diez-Roux 2012). Similarly, a pilot study by Smith et al. (2010), showed participant defined neighbourhoods did not match the 1.6 km Euclidean or network buffers defined by researchers. Furthermore, using GPS data, researchers have demonstrated that older adults walk distances beyond the commonly used 400 and 800 m scales (Prins et al. 2014, Boruff et al. 2012).

Scale is a less obvious issue for activity space methods. For instance, when calculating convex hulls or SDEs the researcher has no direct control over scale. However, scale can be accounted for in these methods by calculating activity spaces for subsets of the input dataset. For instance, creating local SDEs by only using points within a defined distance of home (Boruff et al. 2012), or creating local convex hulls in space and space-time (Lyons 2014). Scale is also relevant to daily path areas when choosing the buffer size for the GPS points.

2.6.1.1 Multi-scale vs single-scale

An additional problem relating to scale is that appropriate scales will likely differ for different locations, activities and population groups (Lupton 2003, Macintyre et al. 2002). Unfortunately, it can be difficult to determine the relevant boundary and size (Carter and Dubois 2010). One approach that has been suggested as a way of overcoming this issue is to use sensitivity analyses to compare effects of variables at different scales (Chaix et al. 2005). However, Spielman and Yoo (2009) found this approach to be ineffective, with little difference in the overall fit of their model across a range of neighbourhood sizes. They suggest that theoretical questions about how people interact with their environment and at what scales should be answered before analytical approaches are used.

While theoretical consideration of appropriate scales is essential, given the sparse theory on the spatial scale relevant to specific health outcomes, exploratory analysis at multiple scales is still important (Diez Roux 2007). Until the choice of scale is theoretically or empirically grounded it has been recommended that researchers report their results at multiple scales of neighbourhood (Brownson et al. 2009).

2.6.1.2 Individual-specific vs uniform scale

Boundaries are typically delineated using a uniform scale for all participants, yet it is possible the size of a neighbourhood or exposure area is shaped by individual characteristics and may vary across individuals (Chaix et al. 2009). Vallée et al. (2015), have called this the 'constant size neighbourhood trap' and investigated this issue by comparing the number of health resources within perceived neighbourhoods and Euclidean neighbourhoods. Their findings showed a large variation in the size of perceived neighbourhoods and they concluded that using spatial units of constant size is a relatively inaccurate way of estimating the actual number of healthcare resources in a neighbourhood.

Further research is needed to explore this issue and determine how well perceived neighbourhoods capture exposure to the environment. We also need to consider and whether the differences found by Vallée et al. are due to the difference between perceived and objective neighbourhoods, the difference between activity space and residential approaches, individual-specific scales, or some combination of these factors.

Lastly, activity space methods may assist in automatically addressing the constant size neighbourhood trap.

2.6.2 Fuzzy vs clear-cut

Neighbourhoods and exposure are inherently vague concepts. It is likely that most ego-centric boundaries are fuzzy, yet current methods of delineation use clear-cut boundaries (Chaix et al. 2009). Ideally, delineation methods would allow for fuzzy boundaries, however there are currently no standard methods for achieving this within GIS.

2.6.3 Oriented vs isotropic

Ego-centric delineation methods usually assume the neighbourhood/exposure area spreads out equally in all directions. In other words, the spatial extents are assumed to be isotropic. Yet this is unlikely to reflect the reality of individual travel and behaviour (Chaix et al. 2009, Matthews 2012). The areas that individuals travel to – and, therefore, are exposed to - are likely to be oriented in the direction of commonly visited destinations.

Delineating oriented buffers is a challenging task. Activity space methods automatically account for anisotropy, but there is still a need to develop oriented ego-centric neighbourhoods especially as activity spaces require detailed location data that is not always available. To date, only one study has proposed an oriented neighbourhood that does not require detailed location data. Madsen et al. (2014), proposed the use of ellipses oriented between home and the central business district as a way of delineating buffers for cyclists.

2.6.4 Time

Time is a consideration not mentioned by Chaix et al. (2009). Most neighbourhood effects on health studies are cross-sectional (Macintyre et al. 2002) and most delineation methods ignore the temporal element. Yet human behaviour – and consequently, exposure to the environment - is dynamic and has both a spatial and temporal component.

Temporal issues in environment and health research include: the time lag between exposure and outcome (e.g., taking into account changes in residence; Blakely and Woodward 2000); the effects of cumulative exposure to the environment; and the amount of time spent in different environments. There is an acknowledged need for longitudinal research on environment and health, and researchers have been calling for greater consideration of individual space-time behaviour when investigating environmental impacts on health (Saarloos, Kim and Timmermans 2009, Kwan 2013, Rainham et al. 2012, Matthews and Yang 2013).

Research is only just beginning to address temporal issues related to exposure to the environment. A growing number of longitudinal studies on the environment and health account for change over longer time periods and across the life course (Villanueva et al. 2013, Giles-Corti et al. 2013, Sarkar, Gallacher and Webster 2013). Similarly, a few studies have explored temporal issues over shorter time frames; for example, through the use of individual mobility data (Wiehe et al. 2008, Shoval et al. 2010).

2.6.5 The modifiable areal unit problem and the uncertain geographic context problem

Two theoretical problems are relevant to the delineation of neighbourhood and exposure in health research: the Modifiable Areal Unit Problem (MAUP); and the Uncertain Geographic Context Problem (UGCoP).

The MAUP highlights how results can vary depending on the division of the study area, either through the zonation - or aggregation - effect (Gold 2006), or the scale effect (Flowerdew et al. 2008). The MAUP has received substantial attention in the geographic literature, and is increasingly acknowledged in the health literature. While the MAUP is concerned with differences in results with different delineation methods, it is not concerned with the question of whether the delineation method adequately captures context.

Whether or not a delineation method captures the true context is the focus of Kwan's UGCoP, which acknowledges that associations between geographic variables and outcome variables may be affected by the precise delineations of an area. Furthermore, it is likely that the delineations in common use deviate from the true geographic context (Kwan 2012a, Kwan 2012b).

2.7 Summary

This chapter provided a broad overview of the literature around the delineation of neighbourhood and exposure; the methods in common use and limitations associated with their application in environment and health research. Later chapters include a more detailed account of literature relevant to the findings reported and discussed in the particular chapter.

As this review has shown, there are numerous existing delineation methods, and the choice of method and scale can make a difference to research results. Yet it is still unclear which of these methods are most appropriate to use in specific circumstances. Therefore, Chapter 3 compares methodological choices in delineation of the residential neighbourhood in a study of the built environment and physical activity.

Another gap identified in this review has been the lack of evidence as to how well different delineation methods capture exposure to the environment. Therefore, Chapters 5, 6, 7, and 8 explore this question in the context of a study of children's mobility.

Finally, this review has identified a need for delineation methods that better capture exposure, yet are not reliant on detailed mobility data (e.g., GPS). Therefore, Chapter 9 proposes several enhancements to the road network buffer that address some of the theoretical issues identified in the literature review and throughout this dissertation.

Chapter 3. The influence of methodological choices on neighbourhood delineation and relationships between the built environment and physical activity

3.1 Introduction

Physical activity is of interest to health researchers because an inactive lifestyle is a risk factor for cardiovascular disease, diabetes mellitus, obesity and other negative health outcomes (Lee et al. 2012). Physical activity is also thought to be a mechanism through which built environments - that is, the places built or designed by humans – can affect chronic disease (Sallis et al. 2012). Therefore, many recent studies have investigated associations between the built environment and physical activity, with evidence accumulating on the health benefits of living in higher density neighbourhoods with well-connected street networks and pedestrian access to a range of amenities (Sallis et al. 2012). Recent reviews have found that various characteristics of the objective built environment were consistently associated with physical activity (including walking) in children (Davison and Lawson 2006), youth (Ding et al. 2011), and adults (McCormack and Shiell 2011), yet inconsistently associated with physical activity in older adults (Van Cauwenberg et al. 2011).

As is the case with much built environment and health research, the magnitude of the associations between the built environment and physical activity are small in comparison to associations between individual factors and physical activity (Bauman 2005). Giles-Corti et al. (2005) have suggested that there is a lack of specificity in measurement in these studies and that the predictive ability of models could be improved if “behaviour-specific measures of the environment were used to predict context-specific behaviours” (p. 175).

An important aspect of increased specificity is improved delineation of neighbourhood and exposure. For instance, many built environment and physical activity studies have modelled relationships between the characteristics of the residential built environment (e.g., operationalised as an 800 m road network buffer around the residential address) with physical activity measured in all locations visited by the participant over the data collection period. This mismatch between context and behaviour may mask the true effect of exposure to various environmental characteristics. Since - as Kwan’s UGCoP states - the true context is often unknown, researchers who want to better delineate context may be required to capture more detailed exposure data (e.g., GPS, travel surveys) and/or conduct sensitivity analyses on a range of context delineation methods and scales. This is further complicated by the fact that the appropriate scale and delineation method is likely to vary by population group, location, outcome measure, and the built environment characteristic of interest (Brownson et al. 2009, Moudon et al. 2006).

This chapter addresses the second aim of this dissertation, which is to explore the influence of different analysis choices on neighbourhood delineation and the relationships between the built environment and physical activity in New Zealand adults. It does this in two ways.

First, it compares seven different delineation methods/scales for a specific population group (adults) and location (New Zealand), with five measures of physical activity and three built environment characteristics (dwelling density, street connectivity, and neighbourhood destination accessibility). While some findings from this analysis may be specific to the sample, other findings may be relevant to other locations and populations and are likely to be useful in the translation of research results into policy and practice and facilitate more effective policy interventions (Learnihan et al. 2011). For example, it is not sufficient for urban designers and planners to know that more shops are associated with higher levels of walking, they also need to know where the shops need to be located – in other words at what distance/scale (Koohsari, Badland and Giles-Corti 2013).

Second, this chapter goes on to focus on road network buffers, comparing different buffering algorithms to determine whether the choice of algorithm makes a difference to results. This builds on work by Forsyth et al. (2012), who compared different network buffering algorithms in a study of the food environment. They noted that different GIS software and different versions of the same software could produce buffers of different shapes and sizes even when using the same scale. They proposed a 'sausage buffer' method of creating road network buffers and demonstrated that the sausage buffer produced similar results to other buffering algorithms when measuring variables associated with the food and physical activity environments and also when measuring the correlations between these variables and relevant outcomes such as physical activity and food purchasing. They also observed that the commonly used ArcGIS (ESRI, Redlands) service area functions are a black box that can change between versions and are not replicable.

The analysis in this chapter adds to Forsyth et al.'s work in a number of ways: 1) it uses different built environment and outcome variables, 2) it uses a greater range of scales, and 3) it determines the impact on the results of statistical models of the association between the built environment and physical activity.

This chapter uses data from the URBAN study. Therefore, the next section provides an overview of the URBAN study methods common to all analyses undertaken in this chapter. It ends with a description of the candidate's contributions to the study.

3.2 URBAN Study methods

3.2.1 Overview of the URBAN Study

The URBAN study was funded by the Health Research Council of New Zealand (07/356) to explore the relationship between the neighbourhood built environment and physical activity in New Zealand. It was a cross-sectional, mixed methods study that was part of a larger twelve country study that used comparable methods to study this relationship internationally (Kerr et al. 2012). The twelve country study was run by the International Physical activity and Environment Network (IPEN).

The URBAN study methods were informed by IPEN protocols for neighbourhood selection, data collection, and the calculation of GIS-based built environment measures. While the study methods have been published elsewhere (Badland et al. 2009), methods and data sources relevant to this thesis are described below and include more detail than in the published manuscript. Ethical approval was granted by Auckland University of Technology and Massey University ethics committees.

3.2.2 Study area and neighbourhood selection

The URBAN study was conducted in four New Zealand cities – North Shore City, Waitakere City, Wellington City, and Christchurch City – between April 2008 and September 2010. A total of 48 neighbourhoods were selected on the basis of a walkability index and levels of Māori population, which was used as a proxy for socio-economic status.

A walkability index was calculated for all urban meshblocks in the study cities. A meshblock is the smallest census area unit used by Statistics New Zealand and urban meshblocks contained approximately 110 people (Statistics New Zealand 2007). Urban meshblocks were initially defined using the 2006 Urban/Rural profile (Statistics New Zealand 2006) and were further refined using zoning data from territorial local authorities. All meshblocks that contained any area zoned 'rural' were excluded.

The walkability index comprised four measures – residential density, street connectivity, land use mix, and retail floor area ratio – and was based on methods described in Leslie et al. (2007) and the IPEN GIS templates (Adams et al. 2012).

Residential density was calculated by dividing the number of private occupied dwellings by the area in residential land use. Meshblock-level dwelling data were obtained from the 2006 New Zealand census and the area in residential land use was estimated using territorial authority zoning data.

Street connectivity was calculated by dividing the number of 3-or-more-way intersections by the area of the meshblock. To minimise edge effects, the meshblock was buffered by 20 m for this measure only. Intersections were derived from road datasets provided by territorial authorities.

Zoning data were used to categorise areas into five different land uses: commercial, residential, industrial, open space, and other. Land use mix was calculated using an entropy equation (D'Sousa et al. 2006), where 0 indicates homogeneity of land use, and a value closer to 1 indicates greater heterogeneity of land use.

Retail floor area ratio was calculated by dividing the area of the footprint of buildings located in retail zones by the land area of the parcels in retail zones. This measure was intended to distinguish between car dominant retail such as big block retail (smaller ratio resulting from a larger land parcel area dedicated to car parking) and pedestrian dominant retail such as strip shopping. However, the utility of the measure is heavily reliant on suitable data. Land use data were not available at a sufficient resolution to identify many of the smaller pedestrian-friendly retail land uses, such as corner shops in suburban neighbourhoods. Therefore, the retail floor area ratio measure was only used in neighbourhood selection and excluded from further analyses. Building footprint and zoning data were sourced from territorial authorities.

The raw measures of residential density, street connectivity, land use mix, and retail floor area ratio were converted into deciles and summed to create the walkability index. Within each city the urban meshblocks were divided into deciles based on the walkability index. Deciles 1-3 were defined as 'low walkability' and deciles 8-10 were defined as 'high walkability.'

The percentage Māori population was assessed for each urban meshblock using 2006 data from the New Zealand census. Within each city the urban meshblocks were divided into deciles based on the percentage Māori population. Deciles 1-3 were defined as 'low Māori' and deciles 8-10 were defined as 'high Māori.'

The study aimed to select three neighbourhoods within each city in each of the following quadrants: low walkability/low Māori; low walkability/high Māori; high walkability/low Māori; high walkability/high Māori. A neighbourhood was defined as five contiguous meshblocks falling within the same walkability/Māori quadrant.

In order to achieve the required sample size of 42 adults per neighbourhood, and assuming a 60% response rate, the neighbourhoods also needed to contain a minimum population of 100 dwellings.

The following process was used to create neighbourhoods from contiguous meshblocks. First, clusters of urban meshblocks with the same walkability/Māori quadrant were created. Meshblocks belonging to clusters with fewer than five contiguous neighbouring meshblocks were excluded from further analyses. Second, a meshblock was randomly selected from the remaining list of eligible meshblocks. Next, the four neighbouring meshblocks with the closest walkability score were sequentially combined with the selected meshblock to form a neighbourhood. These five meshblocks were removed from the eligible meshblocks and the process repeated from the second step until twelve neighbourhoods, three in each quadrant, were selected for each city.

3.2.3 Participant sampling strategy

Participants were recruited by trained interviewers via a door-to-door strategy. GIS was used to generate a random start point within each neighbourhood, and a walking route was defined using a consistent set of rules. Maps were created for the interviewers showing start points, walking routes, and instructions to approach every *n*th household. The household sampling rate was calculated by dividing the dwelling density by the estimated response rate (60%).

42 households were selected in each neighbourhood with one adult (20 - 65 years) recruited in each household. Additional details on participant recruitment and data collection are available in Badland et al. (2009).

3.2.4 Participants

The URBAN study recruited a total of 2033 adults aged between 20 and 65 years of age with a response rate of 44.8%. Residential addresses were geocoded using ArcGIS software. 44 participant's residential addresses could not be located, leaving a total of 1989 participants. Participants provided informed consent/assent.

3.2.5 Demographics, neighbourhood preference, and neighbourhood deprivation

Participants completed a face-to-face computer-assisted personal interview whereby demographic data and self-reported physical activity were collected. Preference for living in a more or less walkable neighbourhood was measured using items developed by Levine et al. (2012). A full description of neighbourhood preference measures in the URBAN study is available elsewhere (Witten et al. 2012). Neighbourhood deprivation was measured using the New Zealand Deprivation Index 2006 provided at the meshblock level (Salmond, Crampton and Atkinson 2007).

3.2.6 Physical activity measures

Objective physical activity was measured using Actical accelerometers (Mini-Mitter, Sunriver, OR, USA), which participants wore on their hips for seven consecutive days during waking hours. The accelerometers recorded physical activity every 30 seconds and participants completed a travel and compliance log for the accelerometer data collection.

The raw output from the accelerometer is called a count (Coulton et al. 2004), with higher counts indicating more intense physical activity. Periods of greater than 59 minutes of consecutive zero counts or where the accelerometer was worn for less than 60 minutes were excluded from analysis.

Two objective measures of physical activity were created based on the accelerometer data: mean number of accelerometer counts recorded per hour worn and, percentage time spent in moderate-vigorous physical activity (MVPA). MVPA was determined using a cut-point of 1500 counts per minute.

Self-report physical activity data were collected using the International Physical Activity Questionnaire – Long Form (IPAQ-LF) (Craig et al. 2003). Three self-reported measures of physical activity measures were created based on this questionnaire: self-reported walking for transport, self-reported walking for recreation, and total self-reported minutes walking for all purposes.

3.2.7 URBAN dataset and spatial data sources

Elements of the URBAN dataset used in this dissertation are presented in Table 3. Spatial data collected to conduct GIS analyses for the URBAN study are presented in Table 4 .

Table 3. Relevant items from the URBAN dataset.

Item	Description	Categories
Identifiers		
Participant ID	Unique participant ID	
Neighbourhood	Unique neighbourhood ID	
City	Unique city ID	
Socio-demographic (individual level)		
Age		1=15-29, 2=30-44, 3=45-54, 4=55-65
Sex		1=male, 2= female
Ethnicity		1=Māori, 2=non-Māori
Highest qualification		1= no qualification, 2=school, 3=post school diploma, 4=tertiary
Marital status		1=never married, 2=married, 3=previously married
Income	Combined annual household income	1=<\$ 40,000, 2=\$ 40,001-60,000, 3= \$ 60,001-80,000, 4=\$ 80,001-100,000, 5= >\$ 100,000
Employment status	Employment status for main occupation	1=full time, 2= part time, 3=unpaid
Vehicle access		1=unrestricted, 2=restricted, 3=no car access

Socio-demographic (area level)		
Neighbourhood deprivation	Meshblock level deprivation index	quintiles: 1=less deprived, 5=most deprived.
Neighbourhood preference		1=strongly prefer walkable, 2=moderately prefer walkable, 3=neutral, 4=moderately prefer less walkable, 5=strongly prefer less walkable
Physical activity		
Self-reported walking for transport	Total minutes walking for transport	
Self-reported walking for recreation	Total minutes walking for recreation	
Self-reported walking	Total minutes walking for all purposes	
Accelerometer measured physical activity	Mean accelerometer counts/hour over a week	
Moderate-vigorous physical activity (MVPA)	Percentage time spent in MVPA	

Table 4. URBAN study spatial data and sources.

Dataset	Source	Year of data collection
Road network	North Shore City Council	2008
	Waitakere City Council	2008
	Wellington City Council	2008
	Christchurch City Council	2008
Planning Zones	North Shore City Council	2008
	Waitakere City Council	2008
	Wellington City Council	2008
	Christchurch City Council	2008
Cadastre	Olivier Consulting	2009
Address points	Olivier Consulting	2009
Building outlines	North Shore City Council	2008
	Waitakere City Council	2008
	Wellington City Council	2008
	Christchurch City Council	2008
Parks	North Shore City Council	2008
	Waitakere City Council	2008
	Wellington City Council	2008
	Christchurch City Council	2008
Public transport stops	Auckland Transport Authority	2008
	Wellington City Council	2008
	Environment Canterbury	2008
Destinations	North Shore City Council	2008
	Waitakere City Council	2008
	Wellington City Council	2008
	Christchurch City Council	2008
	Ministry of Education	2008
	Ministry of the Environment and Land	2005
	Ministry of Health	2008
	Liquor Licensing Authority	2008
	Internet	2005, 2008
	GeoSmart	2008
	Terra Link International	2005

3.2.8 Candidate contributions to the URBAN study

The candidate was a named investigator on the URBAN study. Key contributions included:

- Contribution to the study design and grant application.
- Responsibility for GIS methods, data and analyses.

- Liaison with the IPEN study coordinating centre and modification of IPEN GIS protocols for New Zealand data.

- Contribution as an author/co-author on reports and publications, notably the URBAN study methods paper (Badland et al. 2009), a report for territorial authorities describing the GIS methods used (Mavoa et al. 2009), the IPEN study GIS methods paper (Adams et al. 2014), the main URBAN study results papers (Witten et al. 2012, Oliver et al. 2015b, Hinckson et al. under review), and other papers arising from the study (Hinckson et al. 2014, McGrath et al. under review, Badland et al. 2012, Oliver et al. 2014a).

Further details of candidate contributions to the URBAN study are provided in Appendix A.

3.3 Do different neighbourhood delineations change the results of models of the relationship between the built environment and physical activity?

This section describes the methods and results from the first set of analyses. It compares how model results vary when using different delineation methods/scales, different built environment measures, and different physical activity measures.

3.3.1 Methods

3.3.1.1 Neighbourhood definitions

Two types of neighbourhood definitions – administrative units and road network buffers – were used in this study. Circular buffers were not investigated since they are less appropriate for the built environment measures calculated here. Overall, seven different neighbourhood definitions were created for each participant at a range of scales. Three of the seven areas were based on administrative units: the meshblock; the census area unit, which is comprised of meshblocks in urban areas and contains between 3,000 – 5,000 people (Statistics New Zealand 2007); and the URBAN study neighbourhoods. 36 of the 48 URBAN neighbourhoods were aggregations of five contiguous meshblocks with similar walkability scores. The remaining 12 URBAN neighbourhoods were expanded during participant recruitment to reach the required sample size of 42 adults per neighbourhood. Despite varying numbers of meshblocks, all URBAN neighbourhoods were a similar size.

The four remaining neighbourhood definitions were road network buffers centred on participants' residential addresses and calculated at four scales commonly used in built environment and health research: 500, 800, 1000, and 1500 m (Brownson et al. 2009, Adams et al. 2012). The road network buffers were created using the Service Area function in ArcGIS 9.3 (ESRI, 2013). The road network was supplied by territorial authorities and excluded pedestrian-only paths. Roads that were inaccessible to pedestrians (i.e., motorways and motorway on and off ramps) were removed prior to analysis. The relative sizes of the neighbourhoods are illustrated in Figure 2, which shows neighbourhood definitions for a single participant.

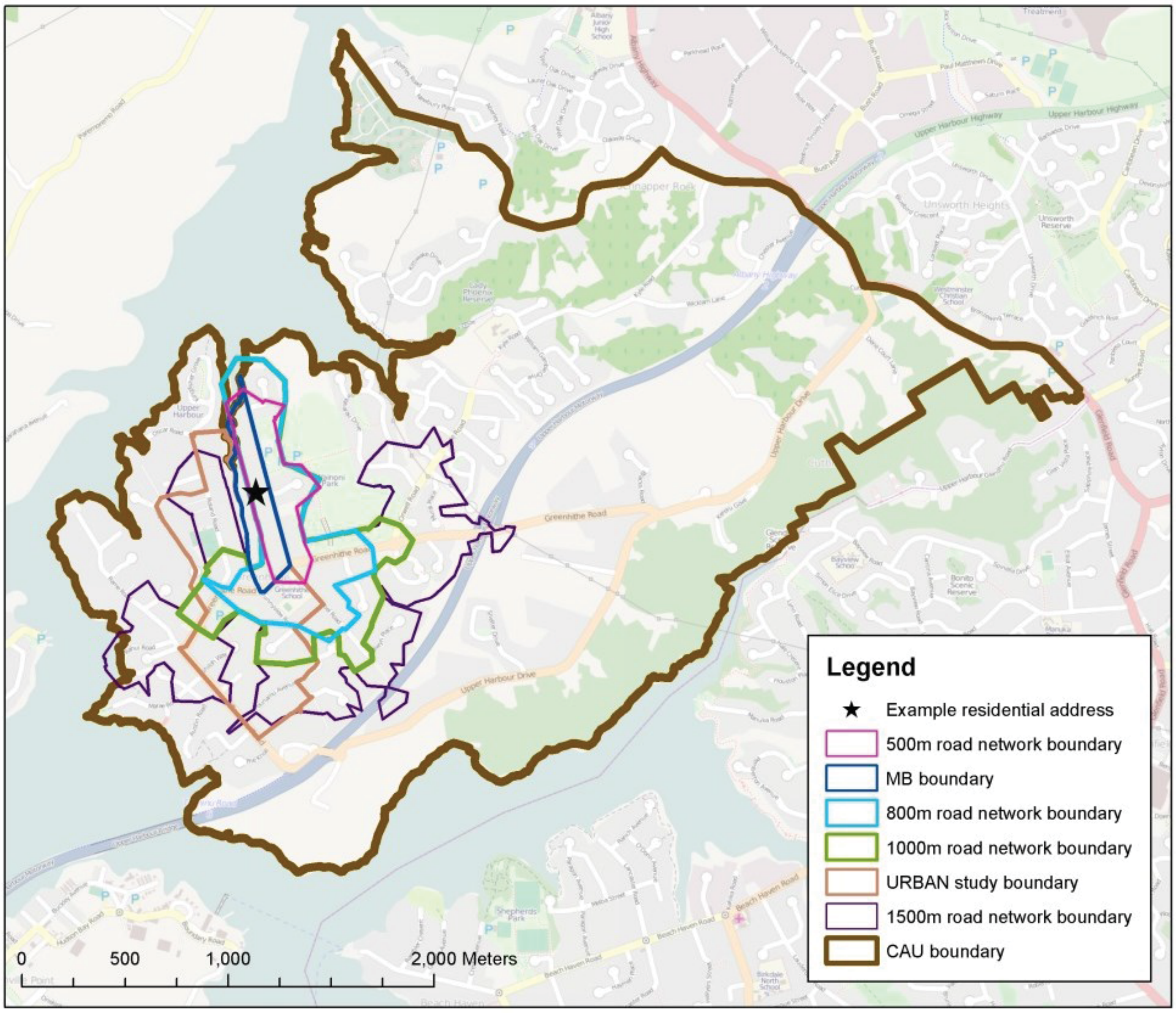


Figure 2. Neighbourhood boundaries for an example participant.

3.3.1.2 Built environment measures

Three built environment measures – residential dwelling density, street connectivity, and destination accessibility – were calculated for every participant for each of the seven neighbourhood definitions. These three measures have been associated with physical activity across different contexts (Sundquist et al. 2011, Kligerman et al. 2007, Witten et al. 2012, Van Dyck et al. 2010).

Dwelling density and street connectivity were calculated as described in the walkability index methods above. Since meshblock boundaries align with all administrative neighbourhoods, the number of private occupied dwellings was easily calculated for this type of neighbourhood delineation. However, meshblock boundaries do not align with road network buffer boundaries. Therefore, the number of private occupied dwellings within each road network buffer was estimated by calculating a weighted average based on the land area of contributing meshblocks.

Destination accessibility was assessed using the Neighbourhood Destination Accessibility Index (NDAI; Witten, Pearce and Day 2011). The NDAI is a measure of access to 31 neighbourhood destinations in eight domains: education, transport, recreation, social and cultural, food retail, financial, health, and other retail. Each domain was assigned a score based on either the presence or density of destinations within a neighbourhood. The NDAI was calculated by summing the weighted domain scores, producing a value between 0 and 31, with a higher score representing better walking access to services and amenities. Since the NDAI was based on presence/absence of destinations, it is expected to increase with increased neighbourhood size.

3.3.1.3 Statistical analyses

The relationships between the built environment and physical activity measures were modelled using linear multi-level mixed effect models to take into account the clustering of individuals within neighbourhoods (defined as the URBAN Study neighbourhood) and cities (neighbourhoods and cities are specified as random effects).

All outcome variables were log transformed to approximate a normal distribution. Therefore, the regression coefficients when exponentiated are the ratio or relative change in the outcome measure for each unit change in the exposure variable.

The relationship between each of the three built environment measures and the five activity measures, were modelled separately for each of the seven neighbourhood definitions (a total of 105 distinct models). Each relationship was assessed by adjusting for individual level factors (sex, age, ethnicity, marital status, education, income, employment, and car access), neighbourhood socio-economic deprivation, and neighbourhood preference (i.e., fixed effects).

The goodness-of-fit of each model was estimated by calculating the marginal R^2 (proportion of variance explained by fixed effects alone) and conditional R^2 (proportion of variance explained by both fixed and random effects; Nakagawa and Schielzeth 2013).

Statistical analyses were conducted in *R* (R Development Core Team 2008) using the 'lmer' function in the 'lme4' package (Bates et al. 2015) to fit the linear mixed models and the 'MuMIn' package to calculate goodness-of-fit (Bartoń 2015).

3.3.2 Results

Descriptive statistics for the size of the seven neighbourhood delineations are shown in Table 5. The meshblock is the smallest neighbourhood, with a median area almost one quarter the size of the next smallest area (500 m road network buffer). The URBAN study neighbourhood is closest in size to the 500 m road network buffer (RNB), and the census area unit falls between the 1000 m and 1500 m road network buffers.

Table 5. Neighbourhood boundary size descriptive statistics.

Boundary type	**Neighbourhood boundary**	**N**	**Median (km^2)**	**Range (km^2)**	**Interquartile range (km^2)**
Administrative unit	Meshblock	272	0.05	1.43	0.05
Contiguous administrative units	URBAN neighbourhood	48	0.30	1.03	0.20
Administrative unit	Census area unit	67	1.83	8.96	1.37
Road network buffer	500 m road network buffer	1,989	0.28	1.03	0.13
Road network buffer	800 m road network buffer	1,989	0.64	0.98	0.31
Road network buffer	1000 m road network buffer	1,989	1.00	1.63	0.51
Road network buffer	1500 m road network buffer	1,989	2.26	3.41	0.95

Table 6 displays the descriptive statistics for the built environment measures for each of these neighbourhood delineations. For the road network buffers, the median street connectivity and dwelling density measures decrease consistently with increasing neighbourhood size. As expected, NDAI measures consistently increase with increasing neighbourhood size.

Table 6. Built environment descriptive statistics for neighbourhood boundaries (n = 1989 adults)

Neighbourhood boundary	**Dwelling density (dwellings/ Ha)**			**Street connectivity (intersections/km^2)**			**NDAI (Score 0 -31)**		
	Median	*Range*	*IQR*	*Median*	*Range*	*IQR*	*Median*	*Range*	*IQR*
Meshblock	11.9	0.6 – 80.8	8.8 – 15.4	25.4	0 - 311.4	3.2 - 48.0	2.0	0 -10.8	0.6 – 5.0
URBAN neighbourhood	11.8	2.1 – 58.3	8.0 - 15.1	33.2	3.7 – 111.7	14.9 – 40.2	5.9	2.5 – 18.9	4.2 – 8.1
Census area unit	8.8	1.3 – 32.1	5.8 – 11.0	25.6	3.6 – 92.3	15.3 – 33.8	9.3	2.2 – 24.1	6.1 – 13.4
500 m RNB	10.2	1.1 – 42.0	8.4 - 12.5	34.1	0 -101.1	24.8 - 42.5	6.4	0 - 24.6	4.1 - 9.4
800 m RNB	9.8	1.9 – 37.3	8.4 - 11.8	32.5	0 - 91.2	25.6 - 39.8	10.2	0 -29.5	6.2 - 14.9
1000 m RNB	9.6	2.4 – 36.6	8.4 - 11.4	31.1	0 - 90.6	25.6 - 38.7	13.9	0 -34.5	7.9 - 19.4
1500 m RNB	9.3	2.5 – 33.0	8.3 – 11.0	29.6	0 - 76.5	25.3 – 38.2	20.7	0 - 40.2	14.6 – 27.4

Table 7 presents descriptive statistics for the physical activity outcome measures. On average, participants in the study spent more time walking for transport than they did for recreation. Mean accelerometer counts per hour had a median value of 8,291.59 and ranged from 281.0 to 30,917.9, with an inter-quartile range of 5,478.5. To put these numbers into context, a participant who is washing dishes for an hour might record counts in the order of 600 (~ 10 counts per minute), while a participant who is continuously playing basketball for an hour might record counts in the order of 282,000 (~ 4,700 per minute; Puyau et al. 2004).

Table 7. Descriptive statistics for the physical activity outcome measures.

Physical activity outcome	**Mean**	**Median**	**SD**
Self-reported walking for transport (total minutes)	25.7	20	54.1
Self-reported walking for recreation (total minutes)	29.4	20	47.0
Self-reported overall walking (total minutes)	55.1	20	73.3
Mean accelerometer counts per hour	9068.7	8291.9	4476.9
% time spend in MVPA	12.4	11	6.8

Table 8 presents the results from each of the 105 fully adjusted models comparing the seven different neighbourhood definitions for three built environment measures and five physical activity measures. Results are reported as the percentage change in physical activity for a one-unit increase in the built environment.

Shaded cells indicate results where the built environment measure was significantly associated with physical activity; that is, where the confidence intervals did not cross zero. The marginal and conditional R^2s are shown in italics and indicate the percentage of variance explained by the model. The magnitudes of the percentage changes reported in Table 8 are not directly comparable across the different physical activity measures. They are, however, comparable between the different built environment measures.

As a general observation, it is worth nothing that effect sizes were small for all models. This is common in built environment research since individual outcomes are more strongly associated with individual predictors. Some of these effect sizes appear meaningful. For instance, for a one dph increase in dwelling density the estimates ranged from a 2.25% to 6.53% increase in walking for transport minutes, which correspond to a 1-2 minute increase in transport walking minutes over a seven day period. Other effect sizes may be less meaningful. For example, 0.27% to 0.45% increases in mean accelerometer counts were associated with increasing the street connectivity by one intersection per square kilometre. However, the main purpose of conducting these analyses was not to identify effect sizes, but to determine whether results differ for the different neighbourhood buffers.

The results for dwelling density show that, for all seven neighbourhood buffers, there was evidence to support an association between dwelling density and two of the physical activity measures: mean accelerometer counts and walking for transport minutes. When examining walking for recreation and total walking measures, there

Table 8. Percentage change (95% CI) and R^2 (marginal/conditional) in fully adjusted models of physical activity, for a 1 unit change in the built environment measures across the seven neighbourhood boundaries.

Built environment measure	**NH definition**	**Mean accelerometer counts/hour % change (95% CI) R^2**	**Percentage time in MVPA % change (95% CI) R^2**	**Self-reported walking for transport (total minutes) % change (95% CI) R^2**	**Self-reported walking for recreation (total minutes) % change (95% CI) R^2**	**Self-reported overall walking (total minutes) % change (95% CI) R^2**
Dwelling density (dwellings / Ha)	MB	0.63 (0.37 – 0.89) *0.08/0.09*	0.47 (0.07 – 0.86) *0.08/0.16*	2.25 (0.76 – 3.73) *0.09/0.16*	3.10 (1.61 – 4.59) *0.07/0.10*	1.93 (0.60 – 3.25) *0.07/0.12*
	UN	0.82 (0.43– 1.08) *0.08/0.09*	0.65 (- 0.05 – 1.36) *0.08/0.16*	4.58 (2.21 – 6.95) *0.11/0.16*	4.39 (2.13 – 6.64) *0.07/0.10*	4.07 (2.0 – 6.1) *0.10/0.13*
	CA	0.87 (0.24 - 1.49) *0.07/0.09*	1.20 (0.20 – 2.19) *0.08/0.16*	4.85 (1.53 – 8.16) *0.09/0.17*	3.11 (-0.36 0 6.57) *0.06/0.09*	1.81 (-1.31 – 4.92) *0.07/0.13*
	B0500	1.05 (0.55 - 1.56) *0.08/0.10*	0.98 (0.15 – 1.80) *0.08/0.16*	4.88 (1.92 – 7.83) *0.10/0.16*	4.25 (1.31 – 7.19) *0.06/0.09*	3.93 (1.27 – 6.59) *0.08/0.12*
	B0800	1.16 (0.53 – 1.78) *0.07/0.09*	1.06 (0.02 – 2.09) *0.08/0.16*	5.12 (1.38 – 8.86) *0.10/0.16*	5.59 (1.98 – 9.20) *0.07/0.09*	4.65 (1.31 – 7.99) *0.08/0.12*
	B1000	1.17 (0.46 – 1.88) *0.07/0.09*	0.83 (- 0.33 – 1.97) *0.08/0.16*	5.20 (0.94 – 9.45) *0.09/0.16*	6.69 (2.61 -10.76) *0.07/0.09*	4.80 (1.01 – 8.59) *0.08/0.12*
	B1500	1.18 (0.40 – 1.97) *0.07/0.09*	-0.01 (-0.76 – 1.82) *0.07/0.16*	6.53 (1.71 – 11.36) *0.10/0.16*	7.48 (2.86 – 12.10) *0.07/0.10*	5.75 (1.43 – 10.06) *0.08/0.12*

Street connectivity (intersections / km^2)	MB	0.02 (-0.01 – 0.01) *0.06/0.09*	0.57 (-0.1 -0.07) *0.07/0.16*	0.18 (-0.14 -0.51) *0.08/0.17*	0.05 (-0.30 – 0.40) *0.05/0.10*	0.10 (-0.19 - 0.39) *0.06/0.13*
	UN	0.27 (0.15 – 0.40) *0.08/0.09*	0.28 (0.05 – 0.53) *0.09/0.16*	1.34 (0.59 – 2.09) *0.10/0.17*	1.16 (0.39 -1.93) *0.06/0.10*	1.04 (0.37 – 1.71) *0.08/0.13*
	CA	0.37 (0.12– 0.63) *0.07/0.09*	0.29 (0.18 – 0.96) *0.09/0.16*	2.13 (0.75 – 3.52) *0.09/0.17*	1.50 (0.03 – 1.93) *0.06/0.09*	1.49 (0.20 – 2.77) *0.07/0.13*
	B0500	0.28 (0.09 – 0.47) *0.07/0.09*	0.27 (0.00 – 0.55) *0.08/0.16*	0.94 (-0.10 – 1.95) *0.08/0.16*	0.90 (-0.17 – 1.96) *0.06/0.09*	0.99 (0.07 – 2.37) *0.07/0.12*
	B0800	0.37 (0.14 – 0.61) *0.07/0.09*	0.41 (0.08 – 0.75) *0.08/0.16*	0.56 (-0.73 – 1.85) *0.08/0.16*	2.08 (0.77 – 3.38) *0.06/0.10*	1.22 (0.07 – 2.37) *0.06/0.12*
	B1000	0.45 (0.25 – 0.70) *0.07/0.09*	0.43 (0.05 – 0.81) *0.08/0.16*	1.50 (0.05 – 2.94) *0.09/0.16*	2.07 (0.62 – 3.53) *0.06/0.09*	1.40 (0.10 – 2.70) *0.07/0.12*
	B1500	0.42 (0.19 – 0.65) *0.07/0.09*	0.23 (-0.18 – 0.63) *0.08/0.16*	2.75 (.125 – 4.24) *0.11/0.16*	2.79 (1.35 – 4.22) *0.07/0.10*	1.53 (0.14 - 2.93) *0.08/0.12*
NDAI (Score 0 – 31)	MB	-1.00 (-2.05 – 0.05) *0.06/0.09*	-0.88 (-2.91 – 0.43) *0.07/0.16*	-1.57 (-6.78 0 3.63) *0.08/0.17*	1.18 (-4.43 – 6.80) *0.05/0.10*	0.05 (-4.69 – 4.79) *0.06/0.13*
	UN	-0.17 (-1.32 – 0.97) *0.06/0.09*	1.17 (-0.81 – 3.14) *0.08/0.16*	-3.61 (-10.06 – 2.83) *0.08/0.17*	1.07 (-5.38 – 7.52) *0.05/0.10*	1.15 (-4.56 -6.97) *0.06/0.13*
	CA	0.88 (0.21 – 1.55) *0.06/0.09*	0.41 (-0.67 – 1.49) *0.07/0.16*	4.64 (0.91 – 8.37) *0.08/0.17*	3.89 (0.09 – 7.70) *0.06/0.10*	4.90 (1.68 – 8.13) *0.07/0.13*
	B0500	0.52 (-0.01 – 1.14) *0.06/0.09*	0.17 (-0.64 -0.97) *0.07/0.16*	1.13 (-2.03 -4.29) *0.08/0.17*	0.92 (-2.47 – 4.30) *0.05/0.10*	3.36 (0.53 – 6.19) *0.06/0.13*
	B0800	0.81 (0.33 – 1.28) *0.07/0.09*	0.82 (0.15 -1.49) *0.08/0.15*	3.51 (1.04 – 5.98) *0.09/0.16*	1.39 (-1.29 – 4.07) *0.05/0.10*	4.01(1.82 – 6.20) *0.07/0.13*
	B1000	0.63 (0.21 – 1.05) *0.06/0.09*	0.64 (0.04 – 1.23) *0.08/0.16*	3.90 (1.76 – 6.05) *0.09/0.17*	1.75 (-0.61 – 4.11) *0.06/0.10*	4.08 (2.18 – 5.97) *0.07/0.13*
	B1500	0.60 (0.21 – 0.98) *0.07/0.09*	0.51 (-0.06 – 1.07) *0.08/0.16*	2.80 (0.77 – 4.82) *0.09/0.17*	0.96 (-1.24 – 3.16) *0.05/0.10*	2.78 (0.98 – 4.58) *0.06/0.13*

was evidence of an association with dwelling density for all neighbourhood definitions except the census area unit. However, when percentage time spent in MVPA was the outcome measure, there was only evidence of an association with dwelling density when measured within a meshblock, a census area unit, a 500 m road network buffer, or an 800 m road network buffer.

When street connectivity was measured within the meshblock there was no evidence of an association with any of the five physical activity measures. Evidence of an association between street connectivity and both mean accelerometer counts and total walking minutes was consistent across the remaining six neighbourhood definitions. When modelling associations with MVPA there was no evidence of an association for the largest road network buffer (1500 m). Conversely, when modelling associations with walking for transport and walking for recreation, there was no evidence of an association for the smaller road network buffers (500 and 800 m in the case of walking for transport and 500 m for recreational walking).

NDAI measured within the two smallest administrative neighbourhoods (meshblock and URBAN) was not associated with any of the physical activity measures. In general, associations between NDAI and physical activity were more likely to be detected when NDAI was measured within larger neighbourhoods. There was only one neighbourhood definition where NDAI was associated with recreational walking: the census area unit.

The number of models that resulted in associations between the built environment and physical activity differed by built environment measure. Dwelling density was most consistently associated with physical activity with 30 out of the 35 models resulting in evidence of an association. 26 of 35 street connectivity models detected an association with physical activity. NDAI was the least consistently associated with physical activity, since only 16 of the 35 NDAI models produced statistical evidence of an association. In general, this suggests that the association between dwelling density and physical activity may be more robust than the associations between street connectivity or NDAI and physical activity.

There was no single neighbourhood definition that resulted in statistical evidence of an association between all built environment and physical activity measures. The meshblock, 500 m, and 800 m road network buffers consistently resulted in evidence of an association between dwelling density and all five physical activity measures. For street connectivity, it was the URBAN neighbourhood, census area unit, and 1000 m road network buffer that produced consistent evidence of an association with physical activity. In contrast, there was no single neighbourhood definition that resulted in consistent evidence of an association between NDAI and all five physical activity measures. The neighbourhood definitions where NDAI was most consistently associated with physical activity were the census area unit, 800 m road network buffer, and 1000 m road network buffer.

When comparing models with the same built environment and physical activity measure, the marginal and conditional R^2s were similar. This indicates that the choice of neighbourhood delineation did not meaningfully change the amount of variance explained by the models.

Although there was no statistical evidence to show that the magnitudes of the association differed for different neighbourhoods, there were scale trends in the point estimates. For example, when looking at the dwelling density and street connectivity models, as the neighbourhood increased in size the magnitude of the effect size also increased for both the administrative unit and road network buffers. In contrast, the scale trend for the NDAI models appears to be nonlinear.

3.3.3 Discussion

The aim of this first part of the chapter was to determine whether different neighbourhood delineations changed results of models of the relationship between built environment and physical activity. As has been suggested in the literature the results of these analyses were influenced by the choice of neighbourhood delineation; different delineations produced different results when modelling the relationship between the built environment and physical activity.

The clearest finding from this study is that the choice of neighbourhood definition, built environment measure, and physical activity measure can all determine whether there is evidence of an association or not. A neighbourhood delineation that is appropriate for one built environment measure may not be appropriate for all built environment measures. Similarly, different delineations may be more appropriate for different physical activity outcome measures. Therefore, it is important to choose neighbourhood definitions carefully, and to report results at a range of scales (Brownson et al. 2009).

The results did not clearly identify a single ideal neighbourhood definition for use in built environment and physical activity research. However, they do suggest the commonly used 800 m road network buffer appears to be an appropriate choice across a range of built environment and physical activity measures, at least for adults. It is also apparent care needs to be taken with the smaller scale neighbourhoods (i.e., smaller than the 800m road network buffer), especially when measuring street connectivity and destination accessibility.

While it is not clear why there was a lack of evidence of associations between street connectivity and physical activity at smaller scales, the lack of evidence at the smaller scales makes sense for the NDAI. Given that neighbourhoods in this study had a minimum population criterion, we would expect residential dwellings to be the most common feature in the study neighbourhoods. The presence of destinations is less guaranteed and may explain why the NDAI measure, which was based on the presence of destinations, was not associated with physical activity at smaller scales.

There may be other explanations for the lack of evidence of associations at the smallest scales. Smaller neighbourhoods are likely to have narrower exposure gradients, making it more difficult to detect effects (Long and Nelson 2013). Additionally, positional accuracy issues – for instance, geocoding and spatial data precision and error – are more influential at smaller scales (Healy and Gilliland 2012). Finally, it is possible that smaller scale neighbourhoods are more relevant to population groups not considered in this study (e.g., non-drivers compared to drivers or children compared to adults). For instance, in a study of geographic area and scale on the relationship between food environment and behaviour, Thornton et al. (2012) found that their smallest neighbourhood (400 m road network buffer) was not significant for the full sample yet reached significance when only households without cars were assessed. This finding is consistent with travel survey data that shows people in non-car households are more likely to use active transport modes than households with access to a car (Barton, Horswell and Millar 2012, Dieleman, Dijst and Burghouwt 2002, Scheiner 2010).

The results of the models of associations between NDAI and recreational walking are also noteworthy. There was only evidence of an association when NDAI was measured within the census area unit (the largest neighbourhood boundary). This could be a spurious result, especially since destination accessibility has not been consistently associated with walking for recreation (Saelens and Handy 2008, McCormack, Giles-Corti and Bulsara 2008, Sugiyama et al. 2012). Alternatively, it could suggest that the scales at which destinations are associated with recreational walking are larger than the scales at which destinations are associated with walking for transport.

It was difficult to determine whether neighbourhood delineation made a difference to the magnitude of the association. Comparing neighbourhoods of different scales revealed different descriptive trends in effect size for the three built environment measures and five physical activity measures. However, these trends were only evident for the point estimates of this sample and there was no statistical evidence that effect sizes vary by neighbourhood definition. In addition, the very small differences in effects sizes were not practically meaningful.

As mentioned earlier, it has been recommended that researchers report GIS-based built environment measures at a range of scales (Brownson et al. 2009), and the results from this chapter support this recommendation. Reporting at a range of scales would assist with greater consistency and comparability across studies. It would also help identify optimal built environment thresholds to support health behaviour for a range of built environment measures, population groups and health behaviours and outcomes (Koohsari et al. 2013).

While it is a worthwhile goal, reporting results at a range of scales may be difficult from a practical perspective. Calculating GIS-based measures of the built environment requires technical staff, specialist software, and sufficient computing power. This can make the calculation of built environment measures at a range of scales prohibitively difficult and expensive. Possible solutions to this problem include sharing GIS resources and knowledge (e.g., sharing scripts and GIS-based models that automatically calculate built environment measures), and the provision of open source tools to calculate built environment measures (Giles-Corti et al. 2014). These mechanisms could reduce the workload and cost for researchers to report results at a variety of scales, and increase comparability of built environment measures between studies.

Reporting results at a range of scales does not preclude the need to determine what scales and ranges are appropriate. An important first step is to consider available theoretical and conceptual models that could assist with decisions about what scales are likely to be most relevant (Diez Roux 2007). Other data - such as time use data (Millward, Spinney and Scott 2013), travel survey data (Yang and Diez-Roux 2012, Burke and Brown 2007), GPS data (Boruff et al. 2012, Zenk et al. 2011), and studies on perceived neighbourhood sizes (Smith et al. 2010) - can also be used to inform the choice of scale by providing information on distances people travel and places they spend time.

When considering the different physical activity measures, the two most general measures – mean accelerometer counts per hour and total walking minutes – were most consistently associated with the built environment across all three built environment measures and all seven neighbourhood delineations. It is likely the mean accelerometer counts and total walking measures will both capture most activity in the residential neighbourhood, whereas the other three physical activity measures are more likely to exclude within-neighbourhood activity. For example, percentage time spent in MVPA was a measure of vigorous physical activity and is the measure most likely to capture physical activity from sport participation and fitness related activities that do not necessarily occur within the residential neighbourhood and may also occur indoors (e.g., working out at a fitness centre).

3.3.3.1 Strengths and limitations

One of the strengths of the analyses presented in this chapter was the comparison of five different physical activity measures, including two objective measures of physical activity. The self-reported walking measures suffer from issues such as poor respondent memory and under-estimation of incidental activities (Dollman et al. 2009). While the objective physical activity measures did not suffer from these issues, they had a different limitation. It was challenging to determine whether effect sizes are meaningful when the outcome measure is accelerometer counts per hour since it is difficult to envision what this measure means in real life. Likewise, this difficulty in interpretation also makes it harder to determine whether the difference in effect size between neighbourhood definitions is consequential.

A limitation relevant to all outcome measures was that the built environment was assessed for the residential neighbourhood, yet the physical activity could have taken place within or beyond the residential neighbourhood.

Another limitation of this analysis is that it did not go beyond the 1500 m scale. It is possible that the built environment is also associated with physical activity at larger scales. However, as the scale increases, the reduced heterogeneity can lead to difficulty detecting effects (Thornton et al. 2012, Long and Nelson 2013).

A further methodological limitation concerns the incomplete representation of where people can travel. When creating road network buffers, road network data were used to represent where people can travel. However, as discussed in Chapter 2, this is an incomplete representation of potential travel paths because it excludes non-road networks that people commonly travel along (e.g., pedestrian only paths, cycle trails). Therefore, the neighbourhood delineations based on road network buffers are likely only subsets of the environment experienced by participants.

Finally, this analysis was limited by imprecise representation of destination data. The location of each destination was represented by a single point, whereas in reality, destinations cover areas of varying sizes. Furthermore, large destinations such as parks and schools, are likely to have several access points. Future analyses would benefit from better representation of destinations and some methods to achieve this have recently been proposed in the literature (Higgs, Fry and Langford 2012, Mavoa et al. 2014).

3.4 Do different buffering algorithms change the neighbourhood definitions?

This section presents the second set of analyses – a comparison of road network buffering algorithms. General URBAN study methods were described in Section 3.2. Additional methods specific to this set of analyses are described in this section.

3.4.1 Methods

3.4.1.1 Buffer creation

Road network buffers were created around the residential addresses of 1989 adults who participated in the URBAN study. Five different types of buffers were created for each participant at ten scales: 400 m, 500 m, 800 m, 1000 m, 1200 m, 1500 m, 1600 m, 2000 m, 2500 m, and 3000 m. After the previous analyses (Section 3.3), the number of scales assessed was increased because it became apparent that fewer data points across a shorter distance made it difficult to detect spatial trends in the results.

Four of the five road network buffer types were calculated using the 'black-box' proprietary service area algorithm in ArcGIS 10.2 software (ESRI, Redlands). The ArcGIS 'Service Area' function has a range of user-specified parameters including: 1) a choice between a 'Generalized' or 'Detailed' service area, 2) a trim option, and 3) a trim distance. Generalised service areas are quick to calculate but are less accurate at the edges and can result in exclusion of islands of unreached elements (ESRI 2013). Detailed service areas are more accurate, but take longer to generate than generalised service areas (ESRI 2013). The edges of service areas can be trimmed to a specified distance of the outer network edges (ESRI 2013).

Table 9 shows the different parameters used for the four ArcGIS buffers calculated in this section.

Table 9. ArcGIS service area types.

ArcGIS service area type	Generalised or Detailed	Trim
Detailed Buffer with No Trim (DN)	Detailed	None
Detailed Buffer with Trim (DT)	Detailed	100 m
Generalised Buffer with No Trim (GN)	Generalised	None
Generalised Buffer with Trim (GT)	Generalised	100 m

The fifth buffer type calculated was the 'sausage buffer' (SB). While the sausage buffer was also calculated in ArcGIS 10.2, the functions used to create it are not proprietary and therefore this approach can be replicated in other software. The sausage buffer was calculated using a 50 m radius from the road centreline (Figure 3).

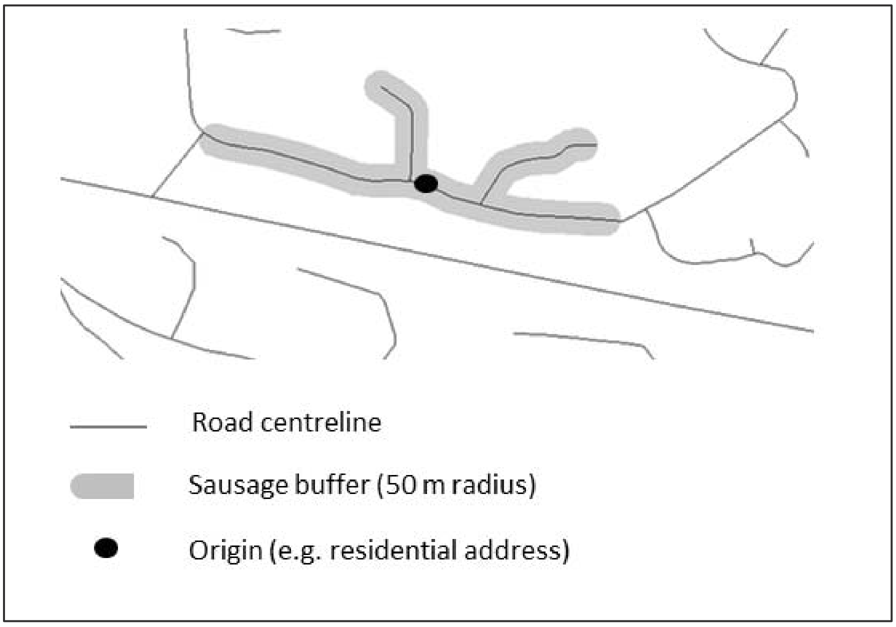


Figure 3. Illustration of a sausage buffer with a 50 m buffer radius.

3.4.1.2 Built environment measures

Six built environment measures were calculated for each buffer: count of 3-or-more-way intersections; street connectivity (i.e., intersection density); count of bus stops; count of dwellings; total park area in the buffer; and percentage of the buffer that is a park. These measures were chosen to represent a range of common types of spatial data measures.

3.4.1.3 Statistical analysis

Descriptive statistics were calculated for the road network buffer areas. Spearman correlations were calculated to compare the built environment measures across the five different buffers for the ten different scales (α = 5%). Associations between the built environment measures and a single physical activity measure - mean accelerometer counts - were assessed using the modelling approach described in the previous section. 300 distinct models were run to capture the combinations of the five types of road network buffer, ten scales, and objective measured physical activity for the six built environment measures. Statistical analyses were conducted in *R* (R Development Core Team 2008).

3.4.2 Results

3.4.2.1 Buffer Area

Table 29 (Appendix B) presents descriptive statistics of the area (km^2) for the five different types of buffer across the ten different scales. These results show that the Sausage Buffers (SB) have the smallest mean and median areas at all scales, with the exception of the 400 m scale, where the Generalised No Trim buffer (GN) had the smallest mean area and the same median area. The difference between the mean and median areas of the Sausage Buffers and the ArcGIS buffers (DN, DT, GN, GT) increases as the scale increases. Across all scales, the Sausage Buffers also have the smallest standard deviations. In other words, there is less variation in size for the Sausage Buffers than for the ArcGIS buffers.

Table 30 (Appendix B) presents the Spearman rank correlation coefficients comparing the area of the different buffer types at each of the ten scales ($\alpha = 5\%$, $p < 0.001$). All correlations between buffer sizes were 'very strong' and ranged from 0.84 between the Detailed No Trim buffer (DN) and the Sausage Buffer (SB) at the 400 m scale, to 1.00 between the Detailed Trim buffer (DT) and the General Trim buffer (GT) at scales greater than 800 m. At the 1000 m, 1600 m, 2500 m, and 3000 m scales the area of the Sausage Buffer was most highly correlated with the areas of the ArcGIS General Trim (GT) and Detailed Trim (DT) buffers. For the remaining scales, the area of the Sausage Buffer was most highly correlated with the area of the

General Trim buffer and next most highly correlated with the Detailed Trim buffer. Sausage buffer areas were least correlated with the Detailed No Trim buffers at all scales.

The magnitude of the correlation coefficients increased as the size of the buffers increased, with the 400 m buffers showing correlations ranging from 0.84 to 0.95 and the 3000 m buffers showing correlations ranging from 0.94 to 1.00. While the correlation between the areas of the Sausage Buffers and all ArcGIS buffers was less than perfect.

Table 30 also shows that - with a few exceptions - the correlation between different ArcGIS buffers was also less than 1.00. In other words, while there were differences between the size of the Sausage Buffers and the ArcGIS buffers, there were also differences in the sizes of different types of ArcGIS buffers.

3.4.2.2 Intersections

Table 31 (Appendix B) shows that the counts of intersections (Cnt) are perfectly correlated between all buffer types when the scale is greater than 500 m. At 400 m and 500 m scales, the correlation coefficients range from 0.98 – 1.00. The correlation coefficients are slightly lower for the intersection density measure (Dns) between all buffer types.

3.4.2.3 Bus Stops

Table 32 (Appendix B) presents the correlation coefficients when comparing the number of bus stops within different buffer types at a range of scales. The correlation coefficients ranged from 0.95 to 1.00, indicating a very strong to perfect correlation between the different buffer types when assessing the number of bus stops. In general, the correlation coefficients increase as the scale increases. Correlations between the sausage buffers and the ArcGIS buffers tended to be slightly lower than correlations between different ArcGIS buffers.

3.4.2.4 Dwelling count

Table 33 (Appendix B) presents the Spearman rank correlation coefficients for the different buffers when measuring dwelling counts. All correlations were very strong to perfect, with correlations higher at larger scales. Correlations between the Sausage Buffer and ArcGIS buffers tended to be slightly lower than correlations between different types of ArcGIS buffer. For example, at scales greater than 1,000 m, dwelling counts for the different ArcGIS buffers were perfectly correlated. At the same scales, the correlations between the Sausage Buffer and the ArcGIS buffers were slightly lower, but still 'very strong' (0.98-0.99).

3.4.2.5 Park Area

Table 34 (Appendix B) presents Spearman rank correlation coefficients for the different buffers when measuring park area and percentage park area. The correlations were lower for park area than for the other built environment measures. Correlations between the Sausage Buffer and the ArcGIS buffers ranged from 0.69 to 0.93 for park area and from 0.76 to 0.93 for percentage park area. In general, the highest correlations between Sausage Buffers and ArcGIS buffers were at the 800 m and 1,000 m scales.

3.4.2.6 Modelled associations with objectively measured physical activity

The associations between the built environment (intersection count, intersection density, bus stop count, dwelling count, park area, and % park area) and objectively measured physical activity were modelled for the five different road network buffers across ten scales. Tables of the results are provided in Appendix C. Results are grouped and discussed below.

For dwelling density (Table 35) and bus stop count (Table 36), results showed that, at all scales, the choice of road network buffer algorithm did not alter whether there was evidence of an association between the built environment measure and physical activity.

While the coefficients varied for the different road network buffers at all scales, the differences were minimal. For dwelling density, at 400 m, the percentage change in physical activity for a one dph increase in dwelling density ranged from 0.87 % (DN buffer) to 1.01% (GT buffer). At the 3000 m scale, the percentage change in physical activity ranged from 2.00 – 2.45%. Again, the lowest percent estimate was for the Detailed No Trim buffer (DN) and the highest for the Generalised Trim buffer (GT). For bus stop count, all models reached significance except for the models at 400 and 3000 m. The magnitudes of the coefficients were very similar for the different types of buffers.

The differences between the Sausage Buffer and ArcGIS buffers were no greater than the differences between the different ArcGIS buffers. Indeed, for the dwelling density models the percentage estimate provided with the Sausage Buffer (SB) was always in the mid-range when comparing the different buffer types.

While not the primary purpose of this analysis, the scale trends observed in the previous analyses were also apparent here. For dwelling density, there was a trend of increasing magnitude in the percent estimates as the scale increased, whereas for bus stop counts, there was a downward trend of coefficient magnitudes with an increase in scale.

For street connectivity (Table 37), total area in park (Table 38) and percentage area in park (Table 39) the choice of buffering algorithm determined whether the models reached significance. Results for street connectivity (Table 37) showed that for the smallest buffers (400 m) there was no evidence of an association when measured with the Detailed No Trim (DN) and Generalised No Trim (GN) buffers. At the 500 m scale, there was no evidence for the Generalised No Trim (GN) buffer). At all other scales there was evidence of associations for all buffer types. There was no obvious difference between the Sausage Buffer and ArcGIS buffers when assessing relationships between street connectivity and physical activity.

Results for total park area (Table 38) showed that from 400 m to 1600 m there were no significant associations for all road network buffers. For larger scales there was variation as to whether different road network buffer produced significant associations between park area and physical activity. At 2000 m, the Generalised Trim (GT) and the Sausage Buffer (SB) produced significant associations. At the 2500 m scale, the Detailed Trim (DT), Generalised Trim (GT) and the Sausage Buffer (SB) produced significant associations, and at the 3000 m scale, the Detailed Trim (DT) and Sausage Buffer (SB) produced significant associations. Where significance was reached, the magnitude of the estimates varied by type of road network buffer, but the differences were, again, minimal. For instance, a range of 0.15 – 0.32% at 2000 m and 0.07 – 0.20 % at 3000 m. Notably the Sausage Buffer was the only type of buffer to reach significance at 2000, 2500, and 3000 m.

Results for percentage park area (Table 39) showed that from 400 – 2000 m there were no significant associations for all road network buffers. At 2500 m and 3000 m the percentage park area measured within Detailed Trim (DT), Generalised Trim

(GT), and Sausage Buffers (SB) resulted in models that detected evidence of an association with percentage park area and physical activity.

3.4.3 Discussion

The results showed that while all five buffer types differed from each other in terms of area and built environment characteristics, whether this made a difference to results depended on the built environment measure. For dwelling density and bus stop count, the built environment measures were very strongly correlated and the choice of buffer did not determine whether models of the association between the built environment and physical activity reached significance.

For street connectivity, while there were very strong correlations between the measures, at smaller scales (400 and 500 m) the choice of buffer could determine whether models reached significance. At larger scales the results were consistent for all buffer types.

Finally, for total area in park and percentage park area, correlations between built environment measures were weaker. Similarly, whether models of the association between parks and physical activity reached significance was in part determined by the choice of buffer.

This suggests that the representation of the built environment measure – for instance points (e.g., intersections, bus stops) versus polygons (e.g., parks) - is important. Figure 4 demonstrates that if a park is represented as a point (centroid) it is less likely to be captured by a road network buffer than if it is represented as a polygon.

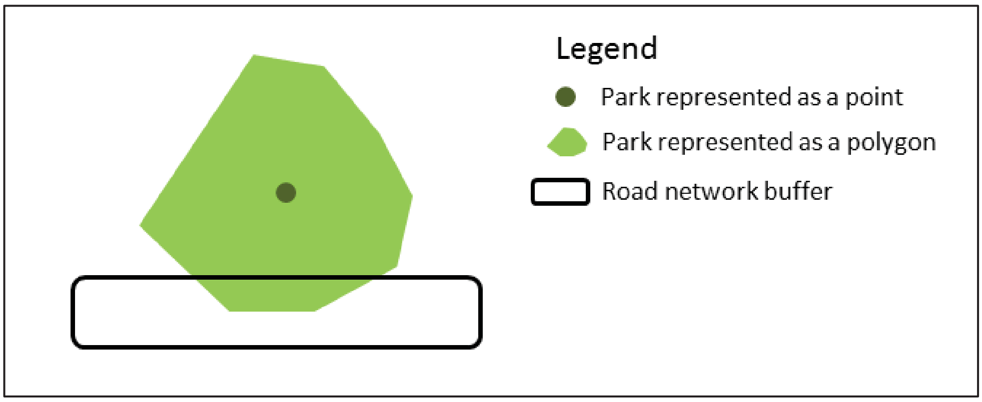


Figure 4. Example park represented as a point and polygon.

The results also illustrated that sausage buffers were consistently smaller than the ArcGIS buffers. This finding is the opposite of Forsyth et al. (2012), and is likely due to the different radial distance used to calculate the sausage buffers. There is no standard radial distance for use in sausage buffers. Therefore, in this dissertation, inspection of the data determined that a 50 m radial distance was appropriate. This contrasts with the 100 m radial distance used by Forsyth et al. (2012).

In summary, choice of spatial data representation (e.g., point versus polygon), built environment measure choice (e.g., count versus density), buffering algorithm (ArcGIS buffers versus sausage buffers), and scale can all change the results of analyses of associations between the built environment and physical activity.

The results of this study support the findings of Forsyth et al. (2012) in recommending the Sausage Buffer as a valid road buffering algorithm, particularly given the transparency and replicability of this method compared to proprietary ArcGIS algorithms. Future research could further compare the buffers by assessing the extent of spatial overlap and how well the different buffers capture exposure to the environment.

The choice of scale appears to have had more of an impact on results than the buffering approach. Furthermore, the analyses in this section undertook a more comprehensive examination of scale (a greater number and range of scales) than previous analyses (i.e., in both the previous section of this dissertation, and in the literature reviewed in Chapter 2). This made scale trends more apparent and future research exploring the role of scale in delineation of neighbourhood would benefit from a similar comprehensive evaluation. Therefore, the results presented here support the previous section in confirming that analyses should be conducted at multiple scales.

Greater consideration needs to be given to analytical choices, particularly how spatial data is represented. For instance, when working with point data, researchers should ensure this is snapped to the road centreline to minimise issues related to choice of buffering algorithm. Alternatively, methods that automatically snap points to the road (e.g., OD-cost matrices) should be considered in lieu of buffering. These alternate analysis approaches might also bypass any issues introduced in the creation of the buffer.

3.5 Methodological commentary

This section reflects on additional methodological issues that arose during the analyses described in this chapter.

3.5.1 Selecting units for the built environment measures

Prior analyses of the URBAN study data transformed all built environment measures by dividing each measure by their standard deviation (SD; Witten et al. 2012). This approach enabled comparison of regression coefficients across different models since each coefficient referred to a 1-SD change (Witten et al. 2012). However, the analyses in this chapter took a different approach; the built environment measures were not transformed prior to the analyses.

This decision was made for two reasons. First, and most importantly, since the standard deviation varies for each neighbourhood delineation, dividing the built environment measures by different standard deviations would make it difficult to compare results across neighbourhoods. Second, modelling the relationship using the original built environment units can make it easier to interpret the results. For example, increasing the dwelling density by one dwelling per km^2 is easier to relate to than increasing the dwelling density by 1-SD.

3.5.2 Measuring street connectivity

Street connectivity was measured by dividing the number of 3-or-more-way intersections within a neighbourhood by the area of the neighbourhood. This appears to be a simple calculation, yet an unforeseen issue arose when calculating street connectivity for administrative units (i.e., meshblock, URBAN neighbourhoods, and census area units).

Administrative unit borders are typically defined by road centrelines, therefore intersections commonly occur on administrative unit boundaries. GIS analyses (e.g., intersect) that count the number of intersections within administrative units assign each intersection to a single meshblock, even if that intersection is on the border of several meshblocks .This means a participant may live near an intersection which may not be included in their neighbourhood delineation. For instance, in Figure 5 meshblock 3 was assigned one intersection and meshblocks 1, 2, and 4 were assigned no intersections. Therefore, participant A would have a higher intersection count – and street connectivity measure – than participant B. This can result in an underestimation of the ‘real’ or ‘experienced’ street connectivity, especially for small meshblocks.

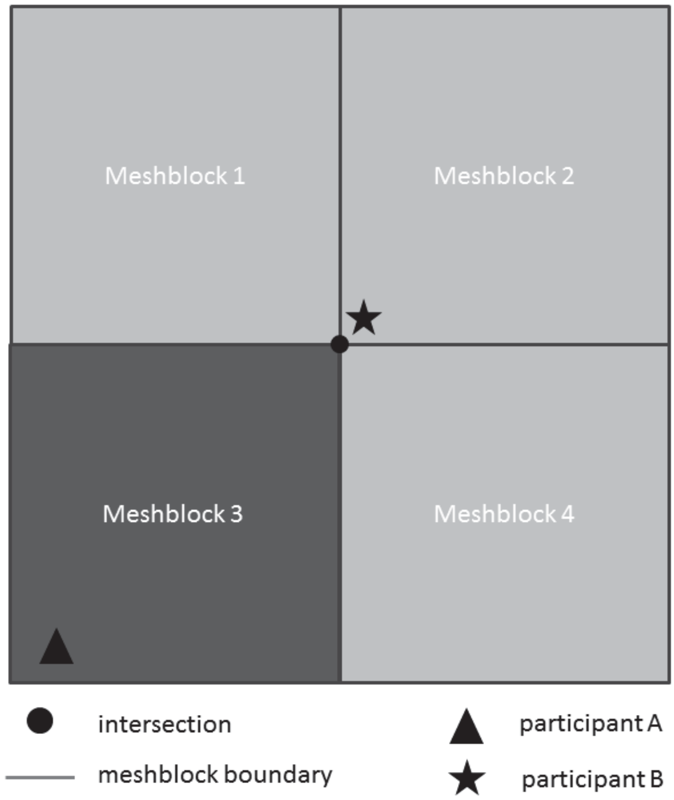


Figure 5. An intersection that borders four meshblocks is assigned to only one meshblock (e.g., Meshblock 3).

The original meshblock level analyses conducted for the URBAN study addressed this issue by buffering the meshblocks by 20 m and calculating street connectivity based on the number of intersections within the buffered meshblock (Figure 6; Badland et al. 2009).

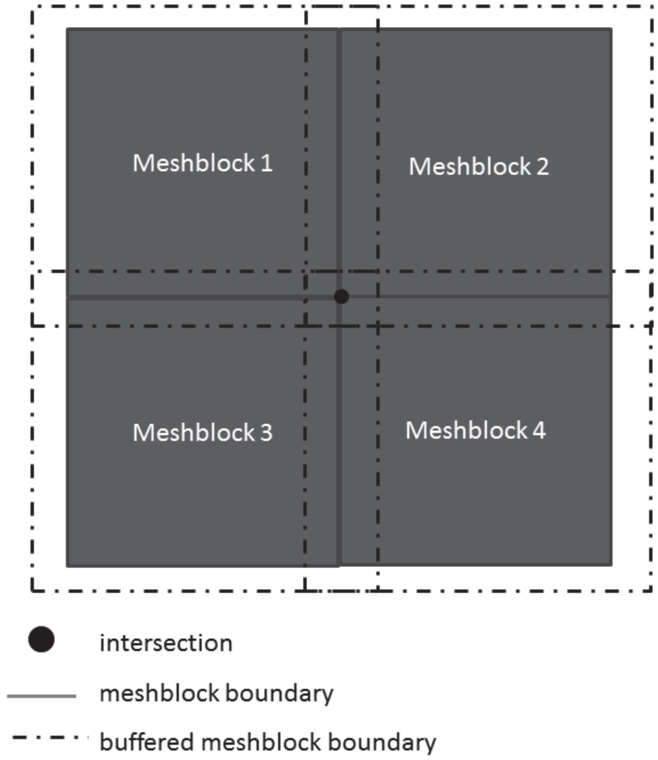


Figure 6. When the meshblock boundary is buffered an intersection that borders four meshblocks is assigned to all four meshblocks.

While the approach of buffering meshblocks addressed the edge issue described above, it also introduced a new phenomenon: a single intersection being counted in multiple neighbourhoods. For example, in Figure 6 a single intersection is counted in four different meshblocks. This is not a problem when using a single neighbourhood delineation in the analysis. However, it produced unexpected results when comparing administrative boundaries of different scales.

This is an example of the MAUP, discussed in Chapter 2. For the same location in space we can arrive at different street connectivity measures if we use different neighbourhood delineations. For instance, in Figure 7 each meshblock has an area of 1 km^2 and the census area unit has an area of 4 km^2. If the number of intersections are counted within buffered meshblocks (e.g., meshblocks buffered by 20 m), then each meshblock would contain 4 intersections, and the resulting street connectivity measure would be 4 intersections per km^2. Yet for the census area unit, the street connectivity would be 2.25 intersections per km^2 (i.e., 9 / 4 km^2). When meshblocks are buffered, larger size differences between administrative units would result in larger differences in street connectivity measures.

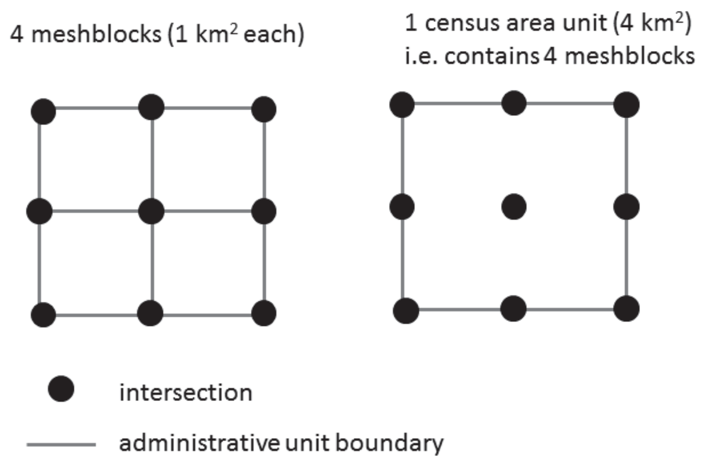


Figure 7. When buffering neighbourhoods, intersections on the borders of neighbourhoods can be counted multiple times.

Therefore, in the analysis reported in this dissertation, the original, non-buffered, meshblock boundaries were used to calculate street connectivity. This avoided double-counting of intersections. Table 10 compares the median street connectivity measures for the administrative unit neighbourhood definitions for buffered meshblocks (not used in this dissertation) and non-buffered meshblocks (used in this dissertation). Note that the URBAN and CAU connectivity measures are the same in the two columns because the boundaries remained the same.

Table 10. Comparison of median street connectivity measures (intersections/km^2) for buffered and non-buffered meshblocks.

	20 m buffered meshblock	Non-buffered meshblock
meshblock	59.6	25.4
URBAN	33.2	33.2
CAU	25.6	25.6

3.6 Discussion and conclusion

This chapter has demonstrated that the delineation method can change the built environment measure and ultimately determine whether associations between the measures and physical activity outcomes are significant or not. It has also highlighted the importance of considering more than just the delineation method. The relationship between spatial data representation, built environment measure, and outcome measure is critical and researchers need to consider methodological choices beyond just the delineation method. While the results did not clearly identify a single ideal neighbourhood definition for use in built environment and physical activity research, they suggested that the commonly used 800 m road network buffer appears to be an appropriate choice across a range of built environment and physical activity measures, at least for adults.

The analysis presented in this chapter has limitations. First, the research presented here was limited by a small range of scales in the earlier analyses (Section 3.3). At the time of analysis the number of scales seemed appropriate and more extensive than in most of the existing literature. However, in hindsight, having only four scales made it difficult to discern spatial patterns. This issue was addressed in subsequent analyses (Section 3.4), where the maximum scale was increased and a greater number of scales were included, making it easier to detect scale trends in the data.

Second, in line with current research comparing delineations, this analysis relied on statistical significance to make conclusions about optimal neighbourhood delineations. It is likely that relying on the results of statistical models alone may not be sufficient to identify appropriate neighbourhood boundaries (Rothman 2014, Gorard 2014), or to determine how well they capture context. Other approaches - such as determining how well a neighbourhood delineation captures exposure to the environment – are needed.

Finally, the analyses in this chapter focused solely on the delineation of potential exposure in the residential neighbourhood. While it was useful to explore the implications of various methodological choices, as discussed in Chapter 2, there is also a need to a) move towards better delineation of actual exposure and b) delineate exposure beyond the residential neighbourhood. Subsequent chapters in this dissertation address these limitations by using GPS data to assess which delineation methods best represent where people travel and spend time.

Chapter 4. Kids in the City study methods

4.1 Introduction

The previous chapter explored the impact of different residential neighbourhood delineations on the results of models of the association between the built environment and physical activity. While it is useful to understand how choice of delineation method may impact research results, it is arguably more important to understand how well delineation methods capture exposure to the environment. As noted in Chapter 2, very little of the research comparing delineation methods has assessed the methods by how well they represent exposure. Furthermore, to date no studies have assessed how well road network buffers – the most commonly used buffer – capture exposure.

The remainder of this dissertation addresses these gaps by determining how well road network buffers represent actual exposure to the environment, exploring activity space delineations, and proposing enhanced methods of delineation (Aims 3 – 5). These issues are explored using data from two cross-sectional, mixed methods studies of the built-environment and children's physical activity. These two studies were combined to create the Kids in the City (KITC) dataset used in this dissertation. This chapter describes relevant methods from these studies.

The quantitative components of the two KITC studies investigated the association between the neighbourhood built environment and children's physical activity and independent mobility (i.e., unsupervised travel and outdoor play). The first study, funded by the Health Research Council of New Zealand (10/497), was conducted in six suburban Auckland neighbourhoods. The second study, funded by a Marsden

Grant (21568 RSNZ), took place in inner city Auckland neighbourhoods. The quantitative data collection for both studies followed the same protocols. Since this thesis uses only the pooled quantitative data, “Kids in the City study” refers to the combined studies, unless otherwise stated.

Although data collection methods have been published elsewhere (Oliver et al. 2011), this chapter describes the methods relevant to the data used in this dissertation and goes into more detail around the methods related to the GIS and GPS data. A pilot study was completed in November – December 2010, in order to test and refine data collection protocols. The full study took place between March 2011 and June 2012. Ethical approval to conduct both phases of the research was provided by Auckland University of Technology, Massey University, and the University of Auckland ethics committees. Informed consent was provided by the school principal, the school board of trustees, the classroom teachers, a parent/guardian, and the child.

Candidate contributions to the KITC study are summarised at the end of this chapter, with details provided in Appendix A.

4.2 School selection

Eight primary schools (years 1-6) and one intermediate school (years 7-8) in Auckland, New Zealand, were recruited for the study. The schools were purposively selected based on their localities and school decile rating, which is an indicator of the socio-economic status of the school catchment area.

Maps of Auckland walkability and destination accessibility (calculated in the URBAN study) were used to identify three pairs of primary schools. Each pair had a similar decile rating, but differing neighbourhood walkability and destination accessibility scores. The remaining three schools were selected because of their location near the Central Business District (CBD).

The difference in school types (primary versus intermediate) and rationale for school selection is a result of the different aims of the two KITC studies. Characteristics of the nine schools are shown in Table 11.

Table 11. Characteristics of participating schools. Source: Ministry of Education 2010 (NZ Ministry of Education 2010).

School ID	School type	Location	Decile	Roll (%, European, Māori, Pacific, Asian/South Asian, Other)	Estimated walkability and access to destinations
1	primary	East	1	287 (1,25,67,7,0)	Low
3	primary	East	1	427 (3,32,61,2,2)	High
4	primary	South	1	514 (0,45,50,5,0)	Low
2	primary	South	1	421 (0,34,64,2,0)	Medium
6	primary	West	5	531(16,19,18,35,12)	Low
5	primary	West	4	290 (12,23,36,23,6)	High
7	primary	Central	8	249 (27,8,5,55,2)	High
9	primary	Central	6	423 (32,16,15,32,5)	High
8	intermediate	Central	9	531 (59,11,10,16,2)	High

Note: some percentages do not add up to 100 due to rounding errors. Decile 1 = low SES; Decile 10 = high SES.

4.3 Participant recruitment

The study aimed to recruit at least 25 children, aged 9-10 years per primary school and 11-12 in the intermediate school. The rationale for this minimum sample size is described in Oliver et al. (2011), but, briefly, it allows for the determination of a physical activity effect between neighbourhoods and also allows for up to 20% data loss. Limited GPS unit availability also restricted the sample size to a maximum of 30 children, however, in the case of school number 9, two data collection sessions were conducted to increase the sample size beyond 30 and meet the additional sample size requirements for the second KITC study.

A classroom-based session was conducted with each class containing appropriately aged students. This session introduced the research team, explained the study process, and demonstrated the research equipment participants would be wearing (i.e., accelerometers and GPS units). The students were given the opportunity to use the GPS units. The aim of this session was to engage children with the study and to allow them to develop rapport with the researchers. Information sessions for parents were also conducted at the school at a time convenient for parents. The research team presented the research process and answered questions at these sessions.

4.4 Data collection

Data collection occurred in two phases: between March and June, 2011, for schools 1-6, and between March and June, 2012, for schools 7-9. Data collection was conducted for one school at a time.

Spatial location was measured using QStarz BT-Q1000 and BT-Q1000XT GPS units (Qstarz International Inc., Taiwan). The main difference between the units was the greater storage capacity of the BT-QT1000XTs. GPS units were worn on a belt and recorded data every 10 seconds. Participants recorded when they put on and took off the belt.

Seven consecutive days of GPS data were collected. Researchers visited participants at their school on six consecutive weekday mornings to collect and check the previous day/s data, charge the GPS units, and download the GPS data. GPS data were downloaded using the QStarz QTravel v1 Travel Recorder software. Both .kml and raw .csv files were generated and saved to laptops. The file sizes of the GPS data files were checked to ensure the units were recording data. Problematic GPS units were immediately replaced with spares in order to minimise data loss. The GPS unit logs were cleared once the data had been saved. After lunch the charged and reset GPS units were returned to the children. On Friday afternoons children took home a GPS charger and instructions to charge the unit each night.

Socio-demographic data were collected from parents/caregivers as part of a 75 item computer-aided telephone interview (CATI), conducted after the completion of data collection in their child's school.

4.5 GIS, GPS, and accelerometer data processing

4.5.1 GPS

The raw GPS data were cleaned and pre-processed using the Physical Activity Location Measurement System (PALMS; Personal Activity and Location Measurement System (PALMS) website 2012). This is a secure website that allows researchers to clean, process, and link accelerometer and GPS data. PALMS cleaned the GPS data, resampled the data at 30 s intervals – enabling linkage with the accelerometer data - and used travel speed to assign a mode of travel (stationary, walk, cycle, vehicle) to each GPS data point.

The GPS data was further processed and linked to accelerometer data using custom R scripts. A subset non-vehicle GPS dataset was extracted, based on the mode of travel being stationary, walk, or cycle.

4.5.2 GIS

The road network data were topologically cleaned. A walkable road network was created by excluding motorways/highways/freeways and on- and off-ramps.

All home and school addresses for each participant were geocoded using ArcGIS 10.0 (ESRI, Redlands). Two home addresses were unable to be geocoded. School addresses were checked visually. Polygon representations were created for all home and school addresses using the land parcel. This is similar to the approach taken by Klinker et al. (2014) who defined the house as the land parcel.

School entrance points were manually digitised based on entrance locations visible in satellite imagery. GPS data were checked against school entrances to ensure that all school entrances used by participants during data collection were captured. The shortest distance from home to the school entrance along the walkable road network were calculated using the OD-matrix function in ArcGIS.

4.6 Candidate contributions to the KITC study

The candidate was a named investigator on the two funded KITC studies. Key contributions included:

- Contribution to the study design and grant application.

- Responsibility for GIS and GPS methods, data and analyses.

- Contribution as an author on reports and publications, notably the KITC study methods paper (Oliver et al. 2011), other methods papers (Mavoa et al. 2011, Mavoa et al. 2012, Oliver et al. 2014b, Badland et al. 2015a, Badland et al. 2015b) , and results papers (Oliver et al. in press, Oliver et al. 2015a).

Further details of candidate contributions to the KITC study are provided in Appendix A.

Chapter 5. GPS inclusion criteria

5.1 Introduction

The previous chapter presented methods from the KITC study, which collected children's seven-day GPS data. The GPS data will be used in subsequent analyses to assess how well delineation methods capture exposure. Therefore, it is important to ensure that the GPS data are as representative of seven-day exposure as possible. Since missing data is a known issue with GPS data (Kerr, Duncan and Schipperijn 2011), this chapter tests a range of GPS inclusion criteria applied to the KITC GPS dataset.

Inclusion criteria are used to determine whether a participant has sufficient data to reliably estimate the behaviours of interest. Within physical activity research, it is standard practice to apply inclusion criteria to accelerometer data. Accelerometer inclusion criteria – also referred to as 'data reduction' or 'minimum wear time' criteria - vary between studies (Masse et al. 2005, Toftager et al. 2013) and researchers have demonstrated that different criteria can change the results across a range of physical activity related outcome measures (Janssen et al. 2014, Toftager et al. 2013).

Inclusion criteria are also an important consideration for GPS data since insufficient data will not represent a participant's mobility behaviours adequately. For instance, if a child only has one hour of GPS from the seven-day data collection in the KITC study, then the GPS data is unlikely to represent the places that child goes in daily life.

Despite this, few built environment GPS studies have reported their GPS inclusion criteria, and there are no standards among those that do. For example, Klinker et al. (2014) excluded the first day of data, weekend data, participants who did not stay at their primary home during data collection, participants who did not have any outdoor data, and participants who had less than one valid weekday of nine hours combined GPS/accelerometer wear time. Alternatively, Robinson and Oreskovic (2013) employed the following minimum inclusion criteria: 1) a valid hour of combined GPS/accelerometer data required a minimum of 10% non-zero accelerometer epochs with matching GPS data points, 2) a valid day of combined data required at least two valid hours, 3) a valid dataset required at least two valid weekdays and one valid weekend day of combined data.

As mentioned above, several studies have investigated the impact of using different accelerometer inclusion criteria. To date, however, no studies have investigated the effects of using different GPS inclusion criteria. While a thorough exploration of different GPS inclusion criteria is beyond the scope of this dissertation, ignoring this issue may to lead to less reliable results. Therefore, three GPS datasets with different inclusion criteria were created and assessed using descriptive statistics. The three datasets were:

1) A complete GPS dataset with less stringent inclusion criteria applied (subsequently referred to as the 'complete GPS dataset').

2) A subset of the GPS dataset with a more stringent inclusion criteria applied to the entire week of GPS data (subsequently referred to as the 'subset GPS dataset 1').

3) A subset of the GPS dataset with the KITC accelerometer inclusion criteria applied to each day of GPS data for each participant (subsequently referred to as the 'subset GPS dataset 2').

The rest of this chapter describes the creation of these three datasets, presents descriptive statistics, discusses issues relating to GPS inclusion criteria, and outlines a strategy for the use of GPS inclusion criteria within this dissertation.

5.2 Methods – creation of the three GPS datasets

Of the 254 participants in the study, five participants did not have any GPS data, leaving 249 participants that could potentially be included in any GPS analyses. One participant lived on an island and attended school on the mainland. This participant was included in both datasets and in later GPS analyses where possible. However, some analyses were unable to be conducted for this participant (e.g., shortest road network distance to school).

5.2.1 Creating the complete GPS dataset

The purpose of the complete GPS dataset was to maximise the number of participants included by applying the following inclusion criteria:

1) The home address was able to be geocoded. Two participants did not meet this criterion.

2) Participants reported a single home address. Three participants did not meet this criterion due to custody being shared on an equal time basis between the mother and father.

3) GPS data were recorded at the home address. Six participants did not record any GPS data at their home address and therefore did not meet this criterion.

4) Three or more hours of GPS data were collected during the seven-day data collection period. Two participants did not meet this criterion.

Travel diary data revealed that some children stayed overnight at relatives' houses during the week. However, since we were unable to determine whether this was a regular occurrence, these children remained in the dataset. This left a total of 236 children in the complete GPS dataset. All these participants had valid GPS and address data.

5.2.2 Creating the subset GPS dataset 1

Since this dissertation will use the GPS data to explore spatial and temporal aspects of where children travel and spend time - with a focus on the environment outside of home and school - it is important to ensure there are sufficient data points on different days of the week and different times of the day. Ideally, this would mean using inclusion criteria with a high minimum number of hours per day for different days of the week; for instance, at least seven hours per day, for a minimum of three weekdays and one weekend day. However, this approach would not take into account the fact that, for weekdays, up to four hours (six hours school day minus two hours of GPS recharging) of the valid GPS data could be recorded at school. School-based GPS data are less useful in determining where children spend time, since GPS data are not needed to tell us that, in general, children spend their weekdays at school during school hours.

Another issue with this ideal approach is that different participants might have bursts of 'good' GPS data at different times of the day and a strict inclusion approach would exclude this otherwise potentially useful data. Therefore, to prioritise non-school GPS data and to maximise the number of participants with included GPS data, the following approach was taken.

First, the GPS data were divided into three categories: weekdays before school, weekdays after school, and weekends. Weekdays before school included GPS points recorded on weekdays, starting from the time the GPS was put on (based on individual wear time data) and ending at the start of school (based on the school start time). Weekdays after school included GPS points recorded on weekdays from the end of school (based on school end time) and ending at the time the GPS was removed for the day (based on individual wear time data). Each school had slightly different start and end times, and these were taken into account when categorising the GPS data. Weekends included all GPS data recorded on a Saturday or Sunday.

Next, the following additional inclusion criteria were applied to the complete GPS dataset:

1) At least two weekdays with at least 30 minutes before school data; AND

2) At least two weekdays with at least two hours after school data; AND

3) At least five hours of total weekend data.

This left a total of 85 participants in the subset GPS dataset 1. The additional inclusion criteria were determined based on a sensitivity analyses (i.e., exploration of options). There was a trade off between inclusion criteria that minimised missing data and inclusion criteria that maximised number of participants.

5.2.3 Creating the subset GPS dataset 2

The second subset GPS dataset was created based on the accelerometer inclusion criteria used in analyses of KITC accelerometer data (not part of this dissertation; Oliver et al. in press). The inclusion criteria were applied to each day's data for every participant, and only days with valid accelerometer data were included in the analyses. On weekdays, the inclusion criterion was at least three hours of data during the non-school part of the day. On weekend days, the inclusion criterion was at least seven hours of accelerometer data (Oliver et al. in press).

The published KITC accelerometer inclusion criteria were applied separately to each day of activity for every participant since we were interested in children's daily physical activity behaviours. However, as stated above, the current purpose is to explore spatial and temporal aspects of where children travel and spend time. Here, the interest is in mobility over a longer period of time than a single day and, therefore, it does not make sense to apply the accelerometer inclusion criteria to the GPS on a day-by-day basis.

Ideally, the GPS inclusion criteria would require that a participant had seven days of GPS data where each day met the accelerometer inclusion criteria. However, only three out of the 249 participants with GPS data met these strict criteria. As above, a sensitivity analysis was conducted to determine appropriate inclusion criteria. To accommodate the need for several days of GPS data, and to ensure that enough children met the criteria, the following process was used:

1) Accelerometer inclusion criteria were applied to each day of GPS data for every child, to determine whether each day had a valid set of data. Weekdays

required at least three non-school hours of GPS data and weekends required at least seven hours of GPS data.

2) Further criteria of a child having at least two valid days of weekday data and one valid weekend day were applied.

This left a total of 48 participants in the subset GPS dataset 2.

5.3 Descriptive statistics for the three GPS datasets

Table 12 presents characteristics of the three GPS datasets, showing the number of participants in each dataset categorised by school, sex, age, ethnicity, number of cars in the household, and shortest road network distance to school. This table shows that, after applying the additional inclusion criterion, only 36% of participants were retained in the subset GPS dataset 1, and 20% of participants were retained in the subset GPS dataset 2.

Table 12. Characteristics of the three GPS datasets.

		Complete Dataset *n*	**Subset GPS dataset 1 *n***	**Subset 1 % of complete dataset**	**Subset GPS dataset 2 *n***	**Subset 2 % of complete dataset**
School						
	1	25	3	12.0	3	12.0
	2	22	4	18.2	0	0.0
	3	23	7	30.4	3	13.0
	4	25	6	24.0	1	4.0
	5	29	12	41.4	8	27.6
	6	23	13	56.5	4	17.4
	7	28	11	39.3	5	17.9
	8	12	5	41.7	4	33.3
	9	49	24	49.0	20	40.8
Sex						
	Female	133	48	36.1	27	20.3

Male	103	37	35.9	21	20.4
Age (years)					
9	68	26	38.2	18	26.5
10	142	45	31.7	23	16.2
11-13	26	14	53.8	7	26.9
Ethnicity					
European	54	26	48.1	20	37.0
Indian/Asian/Other	65	30	46.2	16	24.6
Māori	28	4	14.3	0	0.0
Not stated	13	5	38.5	3	23.1
Other Pacific Islander	42	12	28.6	4	9.5
Samoan	34	8	23.5	5	14.7
Number of Cars					
0	23	5	21.7	2	8.7
1	100	39	39.0	20	20.0
2	73	26	35.6	19	26.0
>= 3	26	10	38.5	4	15.4
Not stated	14	5	35.7	3	21.4
Distance to School (m)					
0 - 400	40	10	25.0	5	12.5
400 - 800	65	27	41.5	16	24.6
800 -1,200	48	11	22.9	5	10.4
1,200 - 2,000	34	13	38.2	6	17.6
2,000 - 10,000	39	18	46.2	10	25.6
> 10,000	9	5	55.6	5	55.6
Not stated	1	1	100.0	1	100.0
Total	236	85	36.1	48	20.2

While the percentage retained in subset GPS dataset 1 varied by all characteristics in Table 12, school attended had the greatest range of percentage retention. Only 12% of children in school 1 were retained in the subset dataset 1, compared with almost 57% of participants from school 6.

There are several possible explanations for these differences between schools. First, data collection progressed in numerical order, that is, the first data collection took place in school 1, the second data collection in school 2, and so on. Identification of faulty GPS units – which resulted in GPS data loss - occurred more frequently at the earlier schools. Second, the earlier schools had children from different socio-economic status (SES): schools 1-4 were low decile (i.e., low SES), schools 5-6 were mid decile, and schools 7-9 were high decile. This may have affected missing GPS data. For example, some children in lower decile schools reported not being allowed to recharge the GPS units at home because of the cost of electricity. Similarly, children living in households with no cars showed less retention for subset datasets 1 and 2.

The percentage retained in subset dataset 2 also varied by all characteristics. However, there was a notable variation in retention by ethnicity. None of the Māori participants and a relatively low percentage of Samoan (14.7%) and Other Pacific Island (9.5%) participants were retained in this dataset. This corresponds to none of the participants from school 2 being retained (school 2 had no European students and only one Asian student).

5.3.1 GPS descriptive statistics

Table 13 presents descriptive statistics for number of GPS points and hours of GPS data for the three GPS datasets. As expected, the stricter the inclusion criteria, the higher the minimum, mean, and median GPS data numbers and hours, and the lower the standard deviation. When using the complete GPS dataset, participants had an average of approximately 34 hours of GPS data, compared to averages of 48 and 55 hours for the subset 1 and subset 2 datasets, respectively.

Table 13. GPS data descriptive statistics.

	Complete dataset (*n* = 236)		**Subset dataset 1 (*n* =)**		**Subset dataset 2 (*n* = 48)**	
	Number of GPS points	Hours of GPS data	Number of GPS points	Hours of GPS data	Number of GPS points	Hours of GPS data
Minimum	395	3.3	2115	17.6	4814	40.1
Maximum	8495	70.8	8495	70.8	8495	70.8
Mean	4038.1	33.7	5765.2	48.2	6568.3	54.7
Median	3799.0	31.7	5859	48.0	6584	54.9
SD	1814.7	15.1	1353.1	11.3	984.5	8.2

Figure 8 compares the distributions of the three GPS datasets in a boxplot of the number of GPS points for each of the three GPS datasets. As the inclusion criteria become stricter and the number of included participants decreases, the distribution of the total number of GPS points becomes narrower.

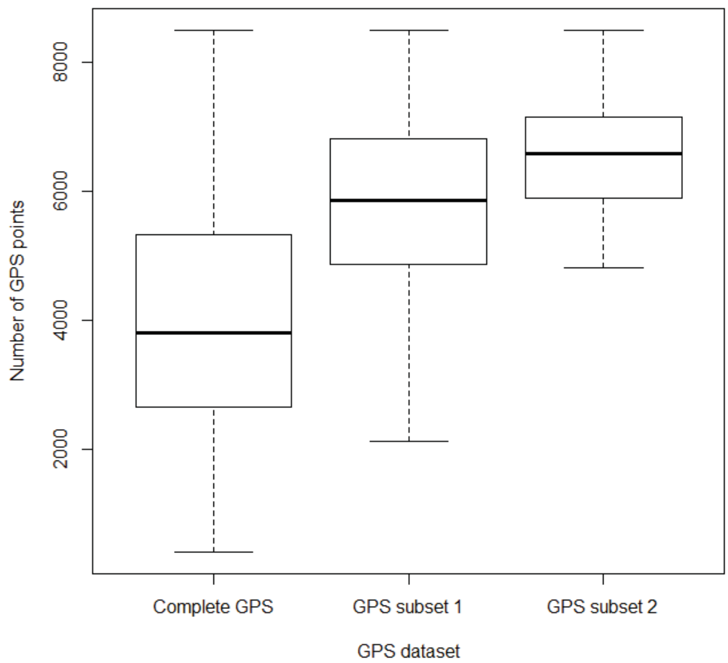


Figure 8 Boxplot of the distributions of the three GPS datasets created with different inclusion criteria.

5.4 Discussion and conclusion

The results described above illustrate that applying GPS inclusion criteria can potentially remove a large number of participants from the dataset. Yet inclusion criteria are important to ensure data are as representative of behaviour as possible. Ultimately, there is a trade-off between strict/ideal criteria and maximising the number of participants included. More comprehensive analysis of this trade-off, along with the development of standardised GPS inclusion criteria, is an important knowledge gap for researchers to address in future research.

As demonstrated in this chapter, applying ideal criteria can leave very few participants in the dataset. In the KITC study GPS data were collected from 254 students, yet only 249 had any GPS data. Applying increasingly strict inclusion criteria dropped the sample sizes to 236, 85, 48, and 3 respectively. This indicates that larger samples are needed when collecting GPS data. A 2011 review of physical activity studies that used GPS data showed that 21 out of 23 reviewed studies had sample sizes less than 185, and over half of the studies had sample sizes less than 50 (Krenn et al. 2011). A more recent review of GPS use in studies of children's physical activity (McCrorie, Fenton and Ellaway 2014) indicates that while sample sizes appear to be increasing, most sample sizes are still smaller than the KITC sample size.

In deciding on appropriate inclusion criteria, it is important to consider the research question and how the GPS data will be used. For instance, it wasn't considered appropriate to use accelerometer inclusion criteria used in the KITC study here, because the accelerometer analyses was designed to investigate children's daily physical activity behaviours, whereas, within the framework of this dissertation, the GPS data will be used to investigate mobility patterns over a longer time frame.

Another consideration in using different inclusion criteria for GPS and accelerometer data is that the nature of GPS data collection – that is, requiring sufficient satellites to be visible - means that there are more gaps in the GPS data than in equivalent accelerometer datasets. Research to address the issue of missing GPS data – for example, through imputation techniques - is needed.

The results demonstrated striking differences in retention of participants by SES and ethnicity. Children of Māori and Pacific Island ethnicity and children at lower SES schools were more likely to have GPS datasets that did not meet strict inclusion criteria. This is likely to have equity implications since Māori and Pacific Islanders and those with lower socio-economic status, also have poorer health (Hefford, Crampton et al. 2005; Pearce and Dorling 2006).

The inclusion criteria used in subset GPS dataset 2 were inappropriate to investigate the research questions addressed in this dissertation. Furthermore, the resulting dataset was too small a sample for robust analysis and was not representative of the KITC sample as it disproportionately excluded Māori and Pacific Island participants, and excluded participants from an entire school. Since, the implications of GPS inclusion criteria are unknown, GPS analyses in the following chapter were conducted on both the complete dataset and subset GPS dataset 1, allowing for more robust interpretation of results.

Chapter 6. How well do road network buffers represent where children spend time?

6.1 Introduction

Road network buffers are the current best practice method of delineating neighbourhood in research investigating associations between the neighbourhood environment and health. Despite this, several researchers have demonstrated that people do not access the entire buffer, and buffers often exclude places where people spend time (Madsen et al. 2014, Villanueva et al. 2012, Basta et al. 2010, Prins et al. 2014). Therefore, this chapter explores how well road network buffers represent where children travel and spend time, using the seven-day GPS data from the KITC study.

A number of studies have compared different delineation methods (see Chapter 2 for a review). Most of these studies compared the area of the buffers (e.g., Crawford et al. 2014, Christian 2012, Zenk et al. 2011, Sherman et al. 2005, Madsen et al. 2014), the built environment measures calculated within the buffers (e.g., Christian 2012, Zenk et al. 2011, Sherman et al. 2005), and the results of associations with the environment and various outcomes and behaviours such as walking (e.g., Boruff et al. 2012, Learnihan et al. 2011), or MVPA (e.g., Jones, Zenk and Matthews 2014). Chapter 3 of this dissertation also compared buffers based on results of associations between the environment and physical activity. While this type of comparison provides evidence of how different buffers impact results, it does not reveal how well the different buffers represent where people travel and spend time (i.e., exposure).

Research on how well different buffers represent mobility and activity is scarcer than research comparing the impact of different buffers on study results. Two studies have compared the spatial overlap of road network buffers with self-defined neighbourhoods and activity spaces; in one case for children (Villanueva et al. 2012) and in the other, for adolescents (Colabianchi et al. 2014). Both studies found very little overlap with road network buffers. While self-defined neighbourhoods are not the same as exposure, these results provide another argument for exploring how well road network buffers represent actual and potential exposure. Indeed, how perceived neighbourhoods interact with both potential and actual exposure is an important question that warrants further research beyond this dissertation.

GPS data provide researchers with the ability to measure how well different delineation methods represent actual exposure to the environment, yet very few published studies have undertaken such comparisons. Robinson and Oreskovic (2013), used GPS data to compare youth-defined and administrative neighbourhoods. They found that, although adolescents perceive their neighbourhoods to be a similar size to census-defined neighbourhoods, the youth-defined neighbourhoods better captured the locations where adolescents spent time. Hirsch et al. (2014), compared three GPS derived activity spaces - SDE, convex hull, and daily path area - with road network buffers and found relatively low percentage overlaps. The maximum overlap was 22.3 % between the 800 m road network buffer and the SDE activity space. Overlap with the 400 m road network buffer ranged from 3.3 – 4.4 % for the three activity space representations.

To date, only one study has used GPS data to assess how well road network buffers represent mobility. Madsen et al. (2014), used GPS data to examine how well a number of buffers – including 1 and 2 km road network buffers around the residential addresses - captured transport cycling behaviour of 331 regular cyclists. They compared buffer sizes with the number and density of GPS points within the buffers. Their results demonstrated that the ellipse shaped buffer between home and the city centre was the most effective, since it had the highest percentage of GPS points per km^2. The city centre in this study was defined as the centroid of the location with the highest density of daily activity destinations.

It should be noted that the existing research which compares different delineation methods focuses exclusively on areas of overlap. However, areas that are excluded from the buffer (i.e., errors of omission) and areas that are included in the buffer but not visited (i.e., errors of commission), may also be relevant.

The rest of this chapter explores how well road network buffers represent children's non-vehicle mobility when compared with the KITC GPS data. The decision to focus on non-vehicle mobility was consistent with the objective to examine how well road network buffers represent exposure. Alignment between the GPS data and road network buffers was assessed using existing methods; namely, overlap between buffers and the number and percentage of GPS points contained by the buffer. The analyses also expand on existing research by specifically assessing the spatial extent of errors of commission and omission.

6.2 Methods

Data collection and GPS data processing were described earlier in Chapter 4. All analyses in this section were conducted using the two GPS datasets described in Chapter 5: the complete GPS dataset (*n* = 236), to which minimum inclusion criteria were applied, and subset GPS dataset 1 (*n*= 85).

The remainder of this section describes the methods used to create road network buffers, create polygon representations of the GPS data, and compare the road network buffers with the GPS data.

6.2.1 Estimating distance travelled from home

To get a sense of how far from home children were travelling and spending time, the number of GPS points within eight distance bands (400, 500, 800, 1000, 1500, 1600, 2000, and 3000 m) were calculated for each participant. These distance bands were calculated using a Euclidean (straight-line) distance. Since each GPS point represents 30 seconds in time, the number of hours spent within each distance band was calculated by dividing the number of points by 120. The purpose of this analysis was to provide context for the subsequent analyses.

6.2.2 Calculating road network buffers around the residential address

Road network buffers at a range of scales (400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000 m) were calculated around participant home addresses, using the walkable road network and the sausage buffer method (described in Chapter 3). A larger number of scales were assessed here compared to Section 3.3 to better assess spatial trends in the results. In built environment and physical activity research, maximum scales of 1600 m are typically used when representing residential neighbourhoods for adults walking. For children, scales of up to 1600 m have also been used (Villanueva et al. 2012). A maximum scale of 2000 m was chosen for this analysis to extend previous scales and also keep the analyses manageable.

6.2.3 Delineating places children went using daily path areas

Polygon-based representations of places children went during the seven-day data collection were created using the non-vehicle GPS point data (see Chapter 4 for a description of how non-vehicle GPS points were specified). Daily path areas were calculated using a similar approach to that described by Zenk et al. (2011). All non-vehicle GPS points were buffered by 50 m and dissolved to create a single polygon for each participant.

There is no standard buffer distance for the creation of daily path areas. For example, other researchers have used 25 m (Krenn, Oja and Titze 2014), 50 m (Boruff et al. 2012, Oliver et al. 2007, Morland et al. 2002), 100 m (James et al. 2014, Ross et al. 2004, Harrison et al. 2014, Saib et al. 2014, Burgoine and Monsivais 2013) , 200 m (Hirsch et al. 2014), and 0.5 mile (approximately 805 m; Zenk et al. 2011). The 50 m buffer was chosen for this analysis because it encompasses the distance a child could travel within the 30 seconds before the next GPS point (39 m - assuming a walking speed of 1.3 m/s; Finnis and Walton 2008). It also allows for the 10 m advertised horizontal error associated with the GPS units (QStarz 2012).

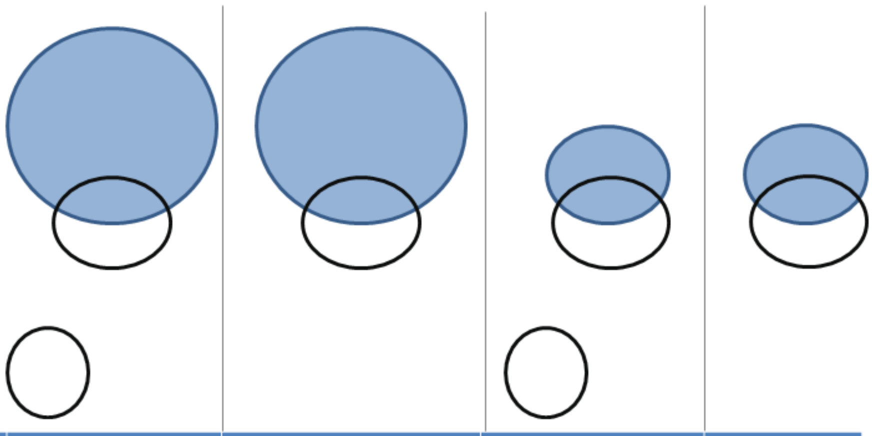
Figure 9 provides an example of a daily path area using actual data for a single participant.

Figure 9. Example of a daily path area.

6.2.4 Comparing GPS daily path areas and road network buffers

One approach to comparing two neighbourhood delineations is to calculate either the area of overlap (e.g., Villanueva et al. 2012) or the percentage overlap (e.g., Hirsch et al. 2014). However, these measures do not completely describe how well one delineation captures a second delineation.

Figure 10 demonstrates that comparing the area – or percentage area - of overlap is not sufficient to determine how well the road network buffers represent the daily path area. Examples A, B, C, and D in the figure all have an identical overlap area yet differ in how well the road network buffers represent the daily path area. The percentage area of overlap also misses some information. For instance, examples A and C have the same percentage of daily path area overlap, yet the road network buffer in example A includes a larger area that was not visited by the participant than example C.



Measure	Example A	Example B	Example C	Example D
Overlap area (km^2)	15	15	15	15
Commission error area (km^2)	85	85	15	15
Omission error area (km^2)	35	15	35	15
Total error area (km^2)	120	100	50	30
% RNB overlapped	15%	15%	50%	50%
% Daily path area overlapped	30%	50%	30 %	50%

Road network buffer (representation of neighbourhood)

Daily path area (representation of where children go)

Figure 10. Illustration of the different measures of geographic overlap.

To gain a more complete picture of how well road network buffers represent where children travel, the overlap between the daily path areas and road network buffers was compared by calculating seven measures of spatial overlap. These seven measures were: overlap area; percentage road network buffer overlap; percentage daily path area overlap; commission error area; omission error area; total error area; and sum of percentage overlap.

Overlap area was calculated using the 'Clip' and 'Calculate Geometry' functions in ArcGIS 10.2 (ESRI, Redlands). The overlap area is the area present in both the GPS daily path and the road network buffer.

The percentage of road network buffer overlap was the overlap area, divided by the total area of the road network buffer, then multiplied by 100. This measure represents how much of the road network buffer is visited by the participant during the seven day GPS data collection. The percentage of daily path area overlap was the overlap area, divided by the total area of the daily path, then multiplied by 100. This measure represents the proportion of places visited by the child that are captured by road network buffers.

The areas representing errors of commission and omission were calculated using the 'Erase' and 'Calculate Geometry' functions. Commission error area refers to the area present in the road network buffer that did not overlap the daily path area. In other words, this is the area captured by the road network buffer that children did not visit during GPS data collection. Omission error area refers to the area present in the GPS daily path that does not overlap the road network buffer – in other words this is the area visited by children but not captured by the road network buffer.

Finally, two composite measures were calculated. Total error area was the sum of the commission error area and the omission error area. The sum of the percentage overlap was the sum of the percentage road buffer overlap and the percentage daily path area overlap.

The road network buffers that best represent where children go will maximise overlap (area and percentages), and minimise the commission, omission, and total error areas (Figure 10).

In addition to calculating overlap measures, road network buffers were assessed by counting the number and percentage of GPS points in each buffer. This is similar to the approach taken by Robinson and Oreskovic (2013) who calculated the percentage of time spent in different neighbourhood definitions. Hours within the road network buffer were derived from the GPS data by dividing the number of GPS points by 120.

6.2.5 Missing GPS data

Missing GPS data is likely to have an impact on any analyses comparing GPS data to road network buffers. For instance, a child may spend substantial time in all parts of a road network buffer. However, if this travel was not recorded by the GPS unit (e.g., due to the child forgetting to wear the unit, or a unit malfunction) then a comparison of the road network buffer and GPS daily path area will underestimate the overlap between the two buffers and overestimate errors of commission. To ensure that the impact of missing GPS data was minimised, all analyses in this chapter were undertaken with two GPS datasets: 1) the complete dataset (236 participants), and 2) the subset GPS dataset 1 (85 participants).

6.2.6 Statistical analysis

Descriptive statistics were calculated for the daily path and road network buffer areas. Paired bivariate analyses using non-parametric Wilcoxon tests ($\alpha = 5\%$) compared the daily path areas with each of the different road network buffers. Statistical analyses were conducted in *R* (R Development Core Team 2008).

6.3 Results

6.3.1 Distance from home

Figure 11 presents results from the analysis of the number of GPS points within Euclidean distances from participant's homes for the complete GPS dataset. For participants who lived less than two kilometres from school, over 90% of GPS points were recorded within two kilometres from home. As expected, participants who lived further from school spent more of their time at greater distances from their home. For the 39 participants who lived between two and 10 kilometres from school, over half their time was spent at distances beyond two km from home. For the nine participants who lived more than 10 km from school nearly three quarters of their GPS points were recorded beyond two kilometres from home.

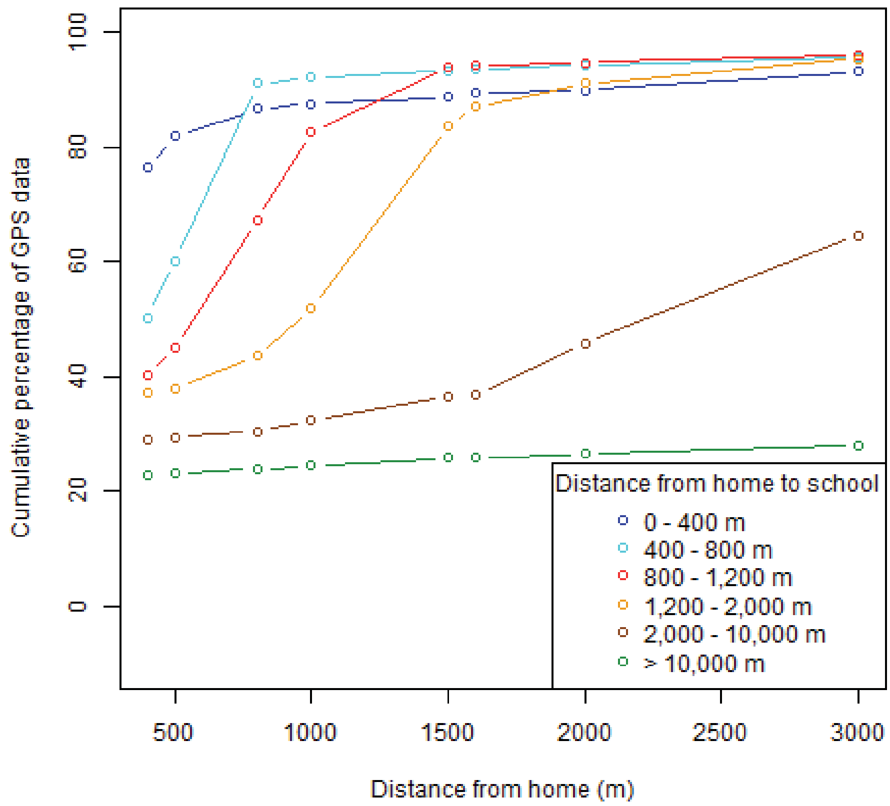


Figure 11. Cumulative percentage of time spent at different distances from home using the complete GPS dataset (*n* = 236).

Figure 12 presents results from the subset GPS dataset. This figure shows a similar pattern, with participants who lived further from school recording a greater percentage of GPS points at distances further from home.

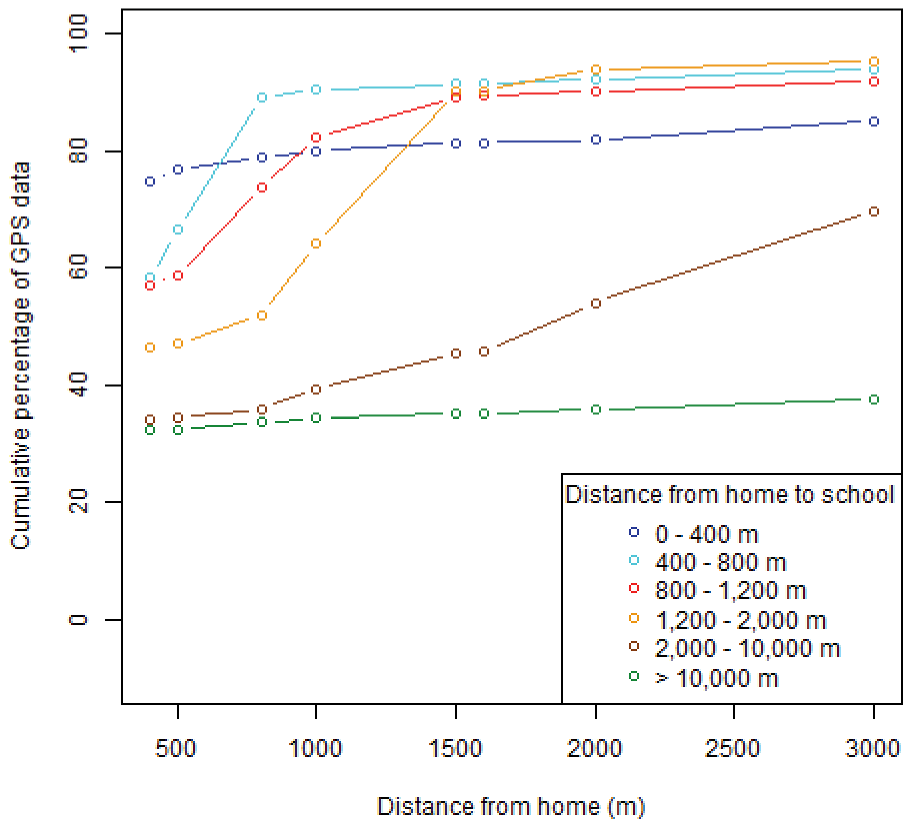


Figure 12. Cumulative percentage of time spent at different distances from home using the GPS dataset with inclusion criteria applied (*n* = 85).

The main differences between the complete GPS dataset and the subset GPS dataset occurred with participants who lived closest to school (< 400 m) or furthest from school (> 10 km). In the subset GPS dataset, participants who lived closest to school had a greater percentage of GPS points further from home than in the complete GPS dataset. Conversely, in the subset GPS dataset, participants who lived furthest from school had a smaller percentage of GPS points further from home than in the complete GPS dataset.

These differences indicate that participants with less complete GPS data – that is, those that did not meet the GPS inclusion criteria – may have accumulated a greater percentage of GPS points near school than further from school. This is likely because research assistants ensured that GPS units were being worn at school every weekday. Outside of school hours, and further from the school, there was no one to remind participants to wear the GPS units, and therefore there is more likely to be missing data at greater distances from the school.

6.3.2 Area of buffers

Table 14 and 15 present descriptive statistics for the areas of the GPS based daily paths and road network buffers. The GPS daily paths represent the places children went during the seven-day GPS data collection, whereas the road network buffers are representations of the residential neighbourhood.

For the complete GPS dataset the mean area of the daily path was significantly different from the mean areas of each of the road network buffers ($p < 0.001$).

For the subset GPS dataset, the mean area of the daily path was significantly different from the mean areas for all but one of the road network buffers ($p < 0.001$). The one exception was the mean area of the 800 m road network buffer, which was not significantly different from the mean area of the GPS daily path ($p = 0.540$)

Table 14. Descriptive statistics of the areas (km^2) of GPS daily paths and road network buffers (RNBs) at different scales. Complete GPS dataset ($n = 236$).

	Mean	Median	SD
GPS daily path	0.45	0.36	0.33
400 m RNB	0.15	0.14	0.05
600 m RNB	0.32	0.30	0.12
800 m RNB	0.57	0.55	0.22
1,000 m RNB	0.90	0.86	0.35
1,200 m RNB	1.31	1.27	0.52
1,400 m RNB	1.80	1.79	0.71
1,600 m RNB	2.36	2.35	0.92
1,800 m RNB	2.99	3.03	1.16
2,000 m RNB	3.69	3.76	1.43

Table 15. Descriptive statistics of the areas (km^2) of GPS daily paths and road network buffers (RNBs) at different scales. GPS dataset with inclusion criteria applied (n = 85).

	Mean	Median	SD
GPS daily path	0.63	0.51	0.41
400 m RNB	0.14	0.14	0.06
600 m RNB	0.32	0.31	0.14
800 m RNB	0.59	0.57	0.25
1,000 m RNB	0.93	0.87	0.38
1,200 m RNB	1.36	1.28	0.53
1,400 m RNB	1.88	1.87	0.71
1,600 m RNB	2.46	2.42	0.92
1,800 m RNB	3.11	3.05	1.15
2,000 m RNB	3.85	3.79	1.44

6.3.3 Overlap of buffers

Table 16 presents the results from the analyses comparing the GPS daily path area polygons and the road network buffers using the complete dataset. Table 17 presents the results for the subset GPS dataset. Both tables demonstrate that, as expected, an increase in the size of the road network buffer is associated with an increase in the areas of overlap and commission errors, and a decrease in the omission error areas.

While these two tables demonstrate that both GPS datasets reveal a similar pattern in terms of overlap between the road network buffers and the daily path area, there are differences between the two datasets. The subset GPS dataset had greater overlap, greater total error and lower errors of omission at all scales. The subset GPS dataset also had lower errors of commission at small scales and greater errors of commission at large scales.

Figure 13 illustrates the differences in magnitude of the overlap, commission errors, omission errors and total errors in the complete GPS dataset. For the 400 - 800 m road network buffers, the magnitude of the errors of commission and omission are similar. However, for the 1000 – 2000 m road network buffers, the errors of commission are orders of magnitude larger than errors of omission. In other words, the larger road network buffers contain substantially greater areas that were not visited by participants than the smaller road network buffers.

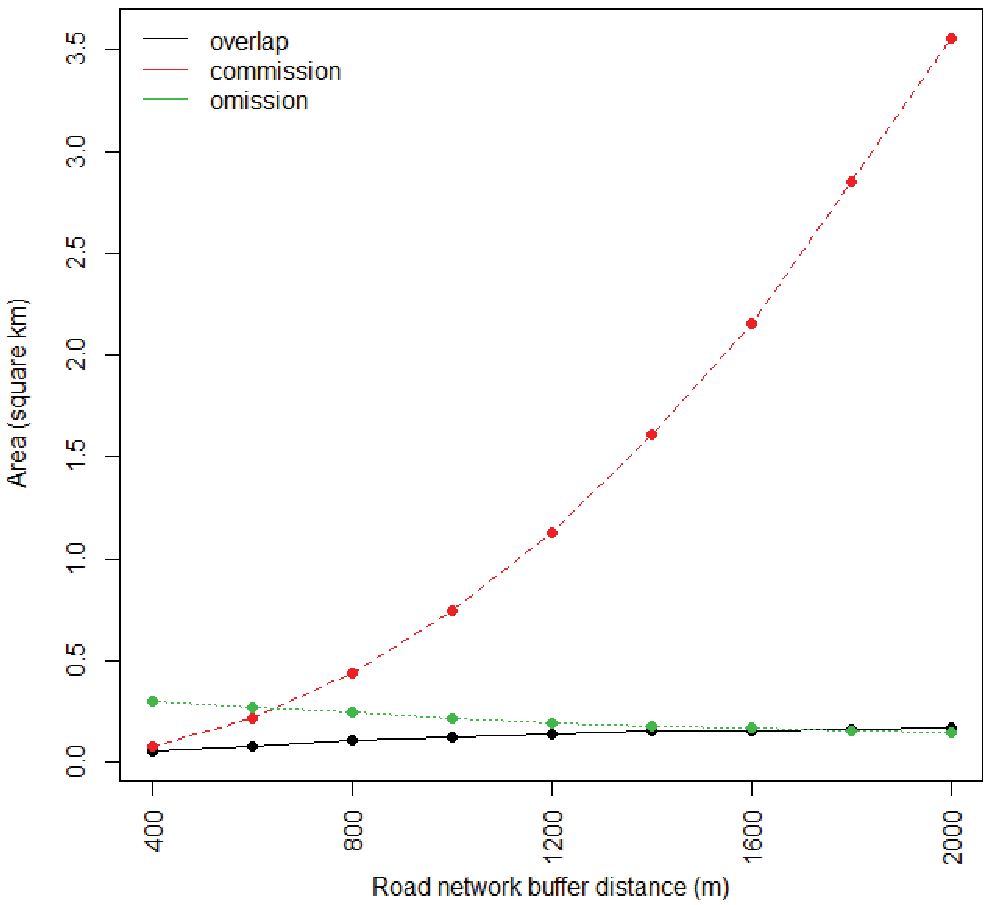


Figure 13. Median overlap, commission error, and omission error areas at different road network buffer distances. Complete dataset (*n* = 236).

Table 16. Comparing the spatial extent of GPS daily paths with road network buffers (RNB): overlap and errors of commission and omission. Complete GPS dataset (n = 236).

	Overlap area (km^2)			**Commission error area (km^2)**			**Omission error area (km^2)**			**Percentage RNB overlap**			**Percentage daily path area overlap**		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
400 m RNB	0.06	0.05	0.04	0.08	0.08	0.04	0.38	0.30	0.31	44.2	40.9	23.6	17.7	16.1	11.4
600 m RNB	0.10	0.08	0.07	0.22	0.22	0.10	0.35	0.27	0.3	31.1	27.9	19.0	25.7	23.7	15.7
800 m RNB	0.13	0.10	0.10	0.44	0.44	0.19	0.32	0.25	0.29	22.8	20.2	15.2	32.8	33.1	19.3
1,000 m RNB	0.15	0.12	0.12	0.74	0.74	0.31	0.29	0.22	0.29	17.6	15.1	12.4	39.0	39.9	21.5
1,200 m RNB	0.17	0.14	0.13	1.13	1.13	0.46	0.27	0.20	0.28	13.9	11.9	10.6	43.7	47.0	22.9
1,400 m RNB	0.19	0.15	0.14	1.6	1.61	0.65	0.26	0.18	0.28	11.2	9.4	9.4	47.2	51.5	23.5
1,600 m RNB	0.20	0.16	0.15	2.14	2.16	0.86	0.25	0.17	0.27	9.3	7.3	8.7	49.5	55.1	23.8
1,800 m RNB	0.21	0.16	0.16	2.75	2.85	1.10	0.24	0.16	0.27	7.8	5.8	8.2	51.6	55.4	24.0
2,000 m RNB	0.22	0.17	0.17	3.44	3.56	1.37	0.23	0.15	0.26	6.6	5.0	7.8	53.1	57.8	24.1

Table 17. Comparing the spatial extent of GPS daily paths with road network buffers (RNB): overlap and errors of commission and omission. Subset GPS dataset (n = 85).

	Overlap area (km^2)			Commission error area (km^2)			Omission error area (km^2)			Percentage RNB overlap			Percentage daily path area overlap		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
400 m RNB	0.07	0.06	0.05	0.07	0.07	0.04	0.55	0.44	0.39	50.7	48.8	24.2	14.0	11.8	8.6
600 m RNB	0.12	0.10	0.08	0.20	0.19	0.1	0.51	0.39	0.38	35.8	33.7	20.0	21.1	19.9	13.1
800 m RNB	0.16	0.12	0.12	0.43	0.42	0.19	0.47	0.36	0.37	26.3	24.3	16.7	27.9	23.8	17.6
1,000 m RNB	0.19	0.15	0.14	0.74	0.70	0.31	0.43	0.32	0.37	20.4	17.9	14.4	33.4	27.8	20.5
1,200 m RNB	0.22	0.16	0.16	1.14	1.11	0.46	0.41	0.27	0.36	16.3	13.7	12.8	37.8	36.4	22.0
1,400 m RNB	0.24	0.19	0.18	1.63	1.61	0.64	0.39	0.25	0.36	13.2	10.5	11.7	41.4	42.2	22.8
1,600 m RNB	0.25	0.20	0.19	2.19	2.15	0.84	0.37	0.24	0.36	11.0	8.3	11.3	43.7	44.5	23.6
1,800 m RNB	0.27	0.21	0.20	2.83	2.86	1.08	0.36	0.23	0.35	9.5	6.6	10.9	46.2	53.0	24.0
2,000 m RNB	0.28	0.21	0.21	3.55	3.59	1.37	0.35	0.22	0.35	8.2	5.5	10.6	47.7	54.7	24.3

Figure 14 illustrates the magnitude of the errors for the subset GPS dataset. The pattern is similar to that of the complete GPS dataset. The main differences being the distance at which the omission and commission areas are equal, and the distance at which the omission and overlap areas are equal. In the complete GPS dataset, omission and commission errors are near equal for a smaller road network buffer (600 m) than in the subset GPS dataset (800 m). Similarly, the overlap and omission areas are also near equal at a smaller road network buffer (1200 m) in the complete dataset, than in the subset GPS dataset (1400 m). The differences between the complete and subset GPS datasets could be due to the different population characteristics in each dataset, however, they may also be due to the amount of missing GPS data as errors of omission and commission may be magnified when there is more missing GPS data.

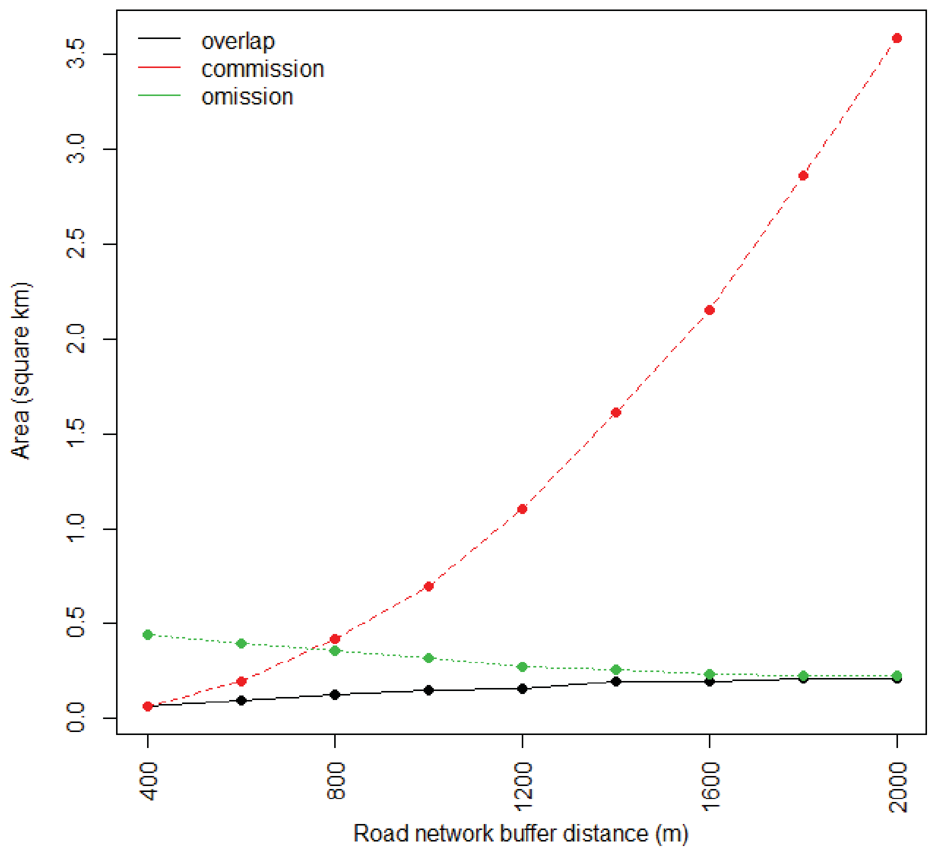


Figure 14. Median overlap, commission error, and omission error areas at different road network buffer distances. Subset GPS dataset (n = 85).

While the areas of overlap, commission and omission are important, it is also important to consider the percentage of the daily path area captured by the road network buffer, and, conversely, the percentage of the road network buffer that contains the daily path area.

Table 16 and Table 17 (above) also present the mean, median and standard deviation of the percentage overlaps. As expected, the percentage of daily path area overlap increases with increased road network buffer size and the percentage of road network buffer overlap decreases with increased road network buffer size.

6.3.4 GPS points/time within buffers

Descriptive statistics for the two GPS datasets were presented in Chapter 5, Table 13. These showed that participants from the subset GPS dataset had, on average, 12 hours more GPS data than participants in the complete GPS dataset.

Table 13 also demonstrated that, on average, the 2000 m road network buffer captures approximately five hours more of GPS activity than the 400 m road network buffer (i.e., 14.51 hours vs 9.81 hours). However, as shown in the previous section, this same change in buffer size adds over 3.3 km^2 of additional error. This error is mostly error of commission; that is, including areas in the neighbourhood boundary that children did not visit (Table 16).

Table 18 summarises the hours spent inside the road network buffers for the complete dataset. The percentage of total recorded GPS time spent within the road network buffer is also provided in this table. For instance, on average, 9.8 hours of time was spent within the 400 m road network buffers. This corresponds to 29.9% of all GPS data. Conversely, on average, 70.1% of the time was spent outside the 400 m road network buffer. Note that the GPS hours only include time when participants were wearing the GPS unit and the GPS unit was recording valid satellite data. Time spent asleep and at home was not included. Furthermore, the time estimates may also exclude time spent indoors when satellite reception was poor.

Table 18 also demonstrates that, on average, the 2000 m road network buffer captures approximately five hours more of GPS activity than the 400 m road network buffer (i.e., 14.51 hours vs 9.81 hours). However, as shown in the previous section, this same change in buffer size adds over 3.3 km^2 of additional error. This error is mostly error of commission; that is, including areas in the neighbourhood boundary that children did not visit (Table 16).

The relatively high standard deviations in Table 18 also demonstrate that, on average, the 2000 m road network buffer captures approximately five hours more of GPS activity than the 400 m road network buffer (i.e., 14.51 hours vs 9.81 hours). However, as shown in the previous section, this same change in buffer size adds over 3.3 km^2 of additional error. This error is mostly error of commission; that is, including areas in the neighbourhood boundary that children did not visit (Table 16).

Table 18 revealed substantial variation between participants. In other words, road network buffers were very good representations of where some participants spent time (i.e., higher percentages of GPS data in road network buffers), and poor representations of where other participants spent time (i.e., lower percentages of GPS data in road network buffers).

Table 19 shows the results for the subset GPS dataset. Here, the standard deviations were higher. On average, the 2000 m road network buffer captured 5.8 additional hours of GPS activity than the 400 m road network buffer.

Table 18. Hours of non-vehicle GPS data recorded inside and outside the road network buffers (RNB). Complete GPS dataset (n = 236).

	Hours of GPS data in RNB					**% GPS data in RNB**				
	Min	**Max**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Mean**	**Median**	**SD**
400 m RNB	0.00	44.62	9.81	7.42	8.89	0.0	86.1	29.9	30.5	20.5
600 m RNB	0.00	44.68	10.95	8.74	9.29	0.0	86.1	33.7	34.3	21.2
800 m RNB	0.00	44.68	11.72	9.47	9.69	0.0	91.0	36.5	38.0	22.3
1,000 m RNB	0.00	44.69	12.40	9.99	9.73	0.0	92.6	39.0	40.8	22.4
1,200 m RNB	0.00	44.74	13.04	10.75	9.90	0.0	92.6	41.2	43.4	22.7
1,400 m RNB	0.00	44.78	13.56	11.20	9.91	0.0	92.6	43.4	45.6	22.7
1,600 m RNB	0.00	44.78	13.89	11.94	10.18	0.0	92.6	44.2	46.1	22.8
1,800 m RNB	0.00	44.78	14.29	12.25	10.26	0.0	92.6	45.5	47.9	22.7
2,000 m RNB	0.00	53.22	14.51	12.43	10.42	0.0	95.5	46.2	48.2	23.0

Table 19. Hours of non-vehicle GPS data recorded inside and outside the road network buffers (RNB). Subset GPS dataset (n= 85).

	Hours of GPS data in RNB					% GPS data in RNB				
	Min	**Max**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Mean**	**Median**	**SD**
400 m RNB	0.00	44.62	15.8	16.24	10.50	0.0	86.1	34.8	38.5	21.3
600 m RNB	0.00	44.68	17.3	19.01	10.56	0.0	86.1	38.4	42.1	21.1
800 m RNB	0.00	44.68	18.3	19.74	11.14	0.0	91.0	40.6	44.4	22.2
1,000 m RNB	0.00	44.69	19.1	20.66	10.96	0.0	92.6	42.5	45.7	21.8
1,200 m RNB	0.00	44.74	19.7	20.87	11.13	0.0	92.6	43.8	47.8	22.1
1,400 m RNB	0.00	44.78	20.3	21.01	11.03	0.0	92.6	45.5	50.0	22.2
1,600 m RNB	0.00	44.78	20.9	21.01	11.41	0.0	92.6	46.6	50.8	22.5
1,800 m RNB	0.00	44.78	21.4	22.07	11.41	0.0	92.6	48.0	51.7	23
2,000 m RNB	0.00	53.22	21.6	22.19	11.62	0.0	95.5	48.4	51.7	23.2

Even though participants with too few GPS points and participants whose home addresses were not verified by the GPS data were excluded from this analysis, Table 19 show that there are participants who did not record any non-vehicle GPS points within road network buffers around their residential address (i.e., there were minimum values of 0).

Participants with no non-vehicle GPS points in the road network buffers were either driven to and from home during data collection, or took non-road routes to and from home. Figure 15 provides an example for one participant. As shown, there are GPS points in the home parcel. However, since road network buffers are centred on road centrelines, these GPS points do not fall within the road network buffer. The participant left the house through a back fence and travelled across vacant land before reaching a road. They returned home using the same route.

This example demonstrates that, in some instances, part of the residential land parcel was excluded from all road network buffers. Inspection of the data also revealed that some participants' residential land parcels were entirely excluded from road network buffers. This occurred when a participant lived down a long driveway/right of way, or if the residential land parcel was large (e.g., when a child lived in a large apartment building or on a block of land with many flats).

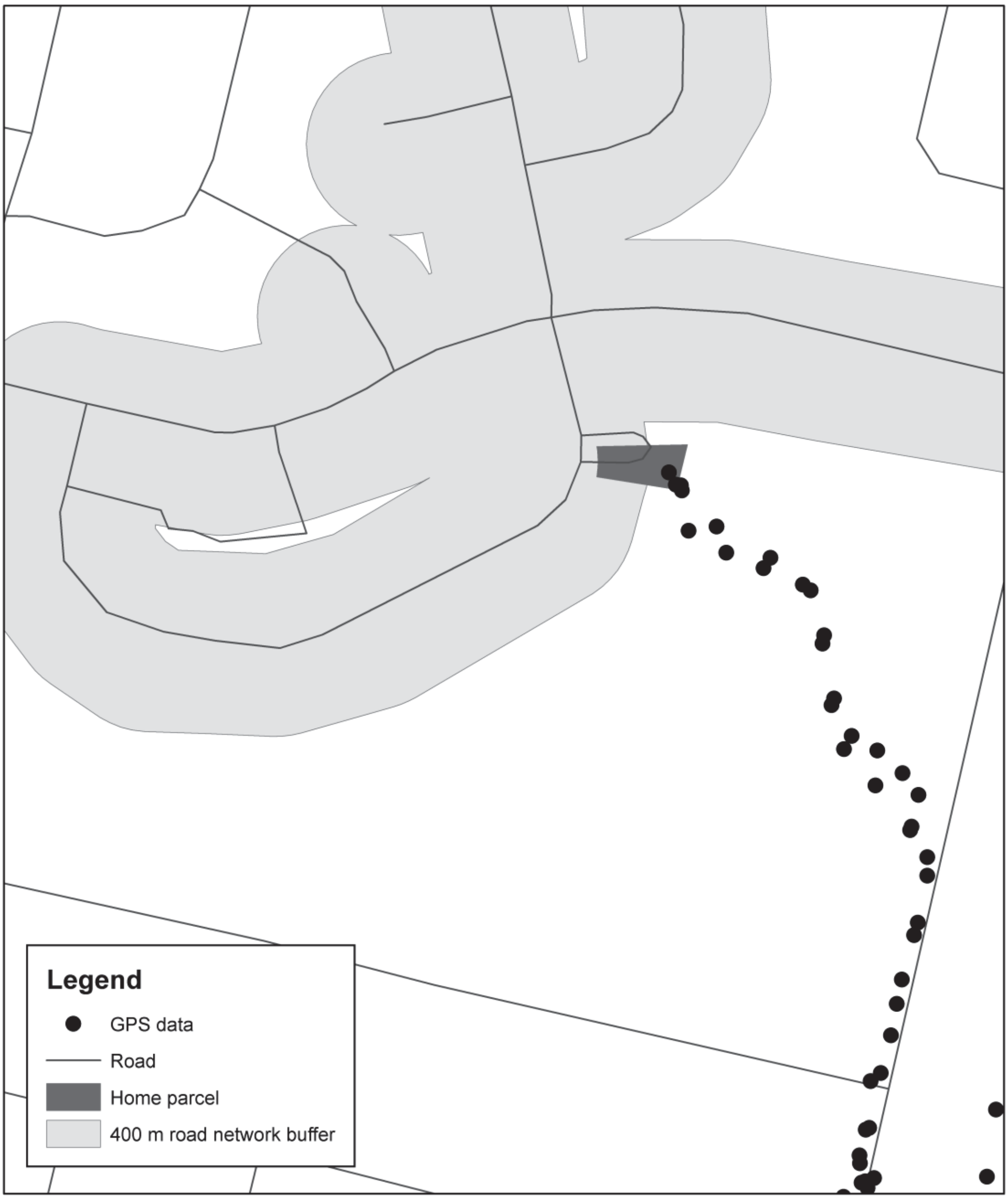


Figure 15. Participant with no GPS data in the 400 m and 600 m road network buffers.

6.3.5 Is there an optimal road network buffer scale?

As shown above, increasing the road network buffer scale necessarily leads to an increase in the overlap, an increase in the commission errors, and a decrease in the omission errors. This tension between an increase in overlap ('good') and an increase in commission errors ('bad') makes it difficult to identify an optimal scale within which to capture children's exposure to the environment.

However, it is possible to gain more insight by combining the overlap measures. Table 20 presents the results for two combined measures: total error area, and the sum of the percentage road network buffer overlap and percentage daily path area overlap.

This table shows that, if the purpose is to minimise the total error area and maximise the percentage overlap, then the 400 m road network buffer is optimal for both the complete GPS dataset and the subset GPS dataset. However, since errors of commission are orders of magnitude larger than errors of omission (refer Figure 13 and Figure 14), this approach to the selection of an optimal network buffer distance is biased against the larger scales. Conversely, the larger buffers are always going to capture more GPS points than the smaller buffers. Ultimately, this means that there is no straightforward way of identifying an optimal scale of road network buffer to capture GPS points (i.e., exposure).

Table 20. Combined overlap measures for the complete GPS dataset (n = 236) and the subset GPS dataset (n = 85).

	Sum of mean % overlap		Mean total error area (km^2)		Number of participants where this buffer has a maximum mean relative density	
	Complete GPS dataset	Subset GPS dataset	Complete GPS dataset	Subset GPS dataset	Complete GPS dataset	Subset GPS dataset
400 m RNB	61.9	64.7	0.46	0.62	202	74
600 m RNB	56.8	56.9	0.56	0.71	14	5
800 m RNB	55.6	54.2	0.76	0.90	3	0
1,000 m RNB	56.6	53.8	1.04	1.18	7	3
1,200 m RNB	57.6	54.1	1.40	1.55	1	0
1,400 m RNB	58.4	54.6	1.86	2.02	4	1
1,600 m RNB	58.8	54.7	2.39	2.57	0	0
1,800 m RNB	59.4	55.7	2.99	3.18	1	0
2,000 m RNB	59.7	55.9	3.67	3.90	0	0

6.4 Discussion

This chapter has examined how well road network buffers capture children's exposure. To answer this, road network buffers at a range of scales were created around children's residential addresses. The extent to which road network buffers captured places children went was assessed by comparing the overlap of the road network buffers with the GPS daily path area. Time spent within road network buffers was estimated by counting the number and percentage of GPS points within each buffer, with each GPS data point representing a 30 second time period.

All analyses were repeated for two datasets: the complete GPS dataset with minimum inclusion criteria applied (n = 236), and the subset GPS dataset with stricter inclusion criteria (n = 85). Comparing the two datasets, the patterns were similar, although there were differences in the numbers. For instance, there were greater errors of omission, greater overlap, and more GPS points captured by road network buffers in the subset GPS dataset. A more rigorous investigation of the impact of different GPS inclusion criteria is needed. Since the subset GPS dataset represented the more stringent inclusion criteria, this dataset will be used in analyses and interpretations for the remainder of this dissertation.

The degree to which road network buffers captured places children went and the time they spent in those places varied for individual participants. Unsurprisingly, larger buffers captured a greater spatial extent of where children travelled to (i.e., less errors of omission) and a greater percentage of the time children spent in those places (i.e., higher percentage of GPS points in the road network buffer). Conversely, the smaller buffers minimised the area in buffers that children did not visit (i.e., less errors of commission).

On average, the 400 m road network buffer captured only 14.0% of the daily path area and 34.8% of the time spent in those places, while even the 2000 m road network buffer captured only 47.7% of the daily path area and 48.4% of the time spent in those places. This demonstrates that road network buffers are not adequate representations of where children go or spend time. While this point has been highlighted by others (Madsen et al. 2014, Villanueva et al. 2012), the analyses in this chapter provide new evidence of the extent to which children's exposure – both spatially and temporally – is captured and excluded by road network buffers at a range of scales.

While it was not possible to determine an optimal road network buffer scale, this chapter has made a new contribution to the literature by specifically assessing errors of omission and commission. Previous studies have only assessed overlap and GPS points contained by buffers. While errors of omission and commission were of a similar magnitude at smaller scales, the errors of commission were up to 12 times larger for the largest road network buffer.

This chapter has provided evidence of the relative gains and losses in choosing one road network buffer scale over another. As mentioned in Chapter 2, 400 and 800 metres are commonly used road network buffer scales for both adults and children. In this sample, using an 800 m road network buffer rather than a 400 m road network buffer captures, on average, 13.9% more of the spatial extent of where children went, and 5.8% more GPS points (i.e., 2.5 hours more activity). Yet the increased capture of time spent within the buffer was offset by an increase in the percentage of the buffer not visited by children (i.e., commission errors). The decision on whether it is more important to capture exposure or minimise errors of commission will depend on the research question.

The analyses in this chapter revealed the unexpected situation whereby residential land parcels contained GPS data, yet road network buffers contained no GPS data.

Exploration of the data revealed a number of situations where road network buffers were not adequately representing children's travel and presence at - or close to - home. These inconsistencies occurred because network buffers are, by definition, centred on roads and may, therefore, exclude part, or all, of the residential land parcel. Similarly, road network buffers may exclude part, or all, of the school land parcel.

Another issue was the failure of road network buffers to capture children's activity and travel that occurred beyond the road network. For instance, one participant used a vacant lot at the back of their house as their route to and from school. These situations occurred because of limitations associated with road network buffers, which are presented in the following section.

6.4.1 Limitations of road network buffers

The limitations of road network buffers identified here arise from analyses undertaken in this chapter. Six limitations were identified and are discussed in detail below. The research acknowledging and/or addressing these limitations is still very sparse, and in some cases non-existent. However, where possible, a review of how these limitations have been acknowledged and addressed in the literature is also included.

6.4.1.1 Road network buffers are typically created around the residential address only

Road network buffers are created around specified origins, typically the residential address. Specifying a single residential origin from which to calculate the buffers ignores other places people travel and spend time in their daily lives such as home, school, shops, and recreational places. This relates to the 'residential trap' (Chaix et al. 2009) and 'local trap' concepts (Cummins et al. 2005) discussed in Chapter 2. This issue is relevant to all types of neighbourhood delineation methods, including road network buffers.

Of the six limitations discussed here, this limitation has received the most attention in the literature with continued acknowledgement of the issue and growing attempts to address it. Researchers are increasingly including non-residential locations and routes in their analyses, and road network buffers are often used to represent these spaces. For instance, researchers have created both home and workplace/school road network buffers (e.g., Thornton et al. 2013), and sometimes also include routes - either shortest path or actual routes from GPS data (e.g., Dalton et al. 2013, Burgoine and Monsivais 2013) - to create a better representation of exposure to the environment. In keeping with the findings of this chapter, this emerging research - along with research evaluating exposure via activity spaces (Villanueva et al. 2012) and GPS tracking (Hirsch et al. 2014, Zenk et al. 2011) - has demonstrated that excluding non-residential locations can lead to underestimation of exposure to various aspects of the environment.

6.4.1.2 Assumption that movement only occurs along the road network

Delineation of boundaries using road network buffers assumes movement occurs only along the road network. Yet, in reality, movement may be restricted in some parts of the road network (e.g., where there are no footpaths), and may also occur beyond the road network. As discussed in Chapter 2, the two studies that have compared pedestrian versus non-pedestrian networks (Tal and Handy 2012, Chin et al. 2008) found that excluding pedestrian routes from street networks can produce different measures of street connectivity and ultimately change the shape and size of the road network buffers.

One approach to addressing this issue is to include pedestrian paths in the network when creating road network buffers. However, the lack of footpath and pedestrian path data is a problem that limits the use of pedestrian network buffers (Badland et al. 2013, Giles-Corti et al. 2014). Given technological advances in the extraction of footpath data from imagery (e.g., Senlet and Elgammal 2012, Smith, Malik and Culler 2013) and the development of methods to approximate footpath locations (Janssen and Rosu 2012), it is likely that digital footpath data will be increasingly available. As this occurs, including pedestrian paths in the network analyses will mitigate this limitation to some extent.

While the increased availability of footpath and pedestrian path data is promising, including footpaths in the network does not entirely address this limitation since people's movement is not restricted to official networks. People can cut across private property, go through public buildings that allow thoroughfare through common areas or public spaces (e.g., shops in the CBD) and cross public open spaces. Such movement beyond the official networks may be especially important for children, who often play in informal or 'found' spaces such as carparks and vacant lots (Thomson and Philo 2004, Berg and Medrich 1980, Carroll et al. 2015) and, therefore, may travel through these informal spaces more frequently. Examples of children's movement in unofficial spaces were evident in the KITC GPS data. For instance, GPS tracks revealed that some children were jumping a fence to get to and from school and others were spending time in, and/or travelling through, vacant lots.

6.4.1.3 Methodological choices can alter the size and shape of the buffer

As discussed in Chapter 3, a range of methodological choices - including those that determine the size and shape of the buffer, the way the spatial data is represented (e.g., points versus polygons), the type of built environment measure (e.g., counts, density, area), and the spatial analysis functions used (e.g., OD matrix versus intersecting points in polygons) - can potentially influence and alter results. This issue has barely been acknowledged in the literature. Only Forsyth et al. (2012) have considered one aspect: the use of different software versions and parameters.

6.4.1.4 Road network buffers are centred on roads, yet in many cases daily lives are not dominated by road environments.

Road network buffers are centred on the road and so excel at capturing the road environment (e.g., intersection density, traffic volume) and the environment in close proximity to the road (e.g., bus stops, footpaths). However, it is likely there are important aspects of daily life that take place at some distance from roads (e.g., work, study, and social and recreational activities). The degree to which road network buffers can capture the non-road environment can depend on the methodological choices discussed above (e.g., road width, algorithm used, data representation choices, polygon versus point). This limitation has not been discussed in the literature.

6.4.1.5 Road network buffers are usually isotropic and do not allow for aspects of the environment to alter their size and shape

In most instances, road network buffers are isotropic. They are created around an origin point and expand equally in all directions along the road network. This ignores the fact that accessibility and exposure are often oriented towards a certain direction. For example, roads in some directions may be more or less accessible than others (e.g., due to slope, presence of pedestrian crossings, traffic light phasing). Mobility patterns and, therefore, exposure to the environment are also likely to be directional. People may choose to travel in certain directions more than others due to characteristics of the network (e.g., traffic, presence of footpaths), the surrounding environment (e.g., slope, presence of destinations of interest, presence of graffiti, crime, land use, public transit stop), and individual factors (e.g., relative location of workplace/school, possession of a driver's license and access to a car).

The problem of using symmetrical representations of neighbourhood to represent asymmetrical movement and exposure was discussed in Chapter 2 and has been acknowledged in the literature (Madsen et al. 2014, Chaix et al. 2009). Some researchers have attempted to address asymmetrical delineations explicitly. For example, Madsen et al. (2014), developed cycling oriented towards the CBD. Alternatively, delineating the asymmetry of daily life can be achieved by using activity space methods. To date, no one has proposed or calculated anisotropic road network buffers.

6.4.1.6 Measuring the built environment within a road network buffer ignores spatial patterning within the buffer

Road network buffers are often created so that researchers can measure characteristics of the built environment within the buffer. However, this ignores any variation or spatial patterning of the built environment within the buffer.

Figures 16-18 illustrate some of the issues and aspects of the built environment that are not being captured with current buffering approaches. This figure shows an example residential road network buffer at a constant scale. Figure 16 demonstrates that the built environment can vary within a road network buffer. Each of the three examples provided has the same destination count and the same destination density, yet real access to destinations varies.

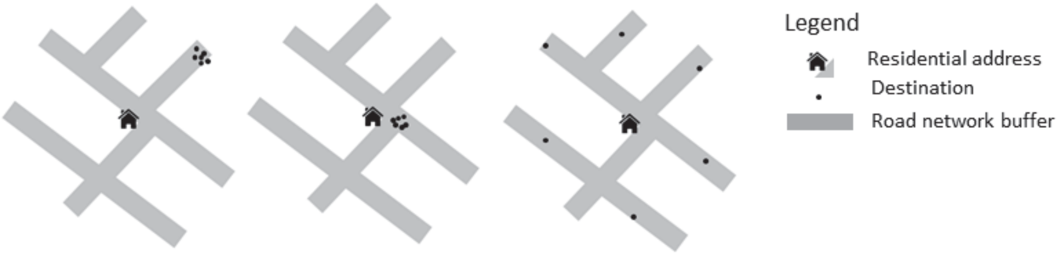


Figure 16. Additional road network buffer limitations – part 1.

The three examples in Figure 17 have the same destination count, the same destination density, and the same destination locations, but, again, the real access differs for each example.

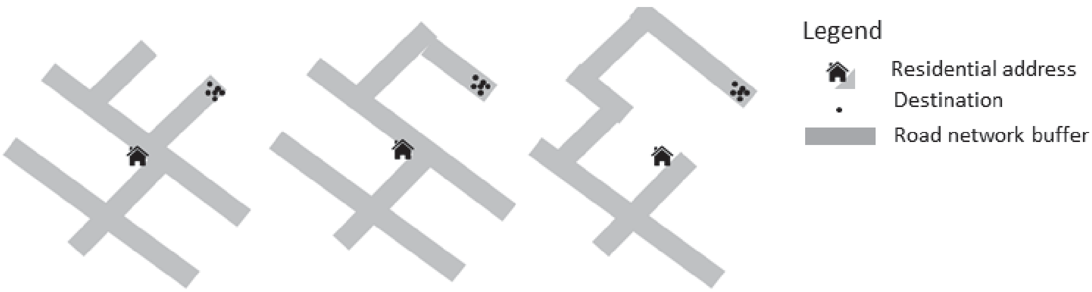


Figure 17. Additional road network buffer limitations – part 2.

In Figure 18, the three examples shown demonstrate the same destinations located on different road networks. While the real potential access to destinations is the same for each example, the destination density differs because of the different road network buffer areas.

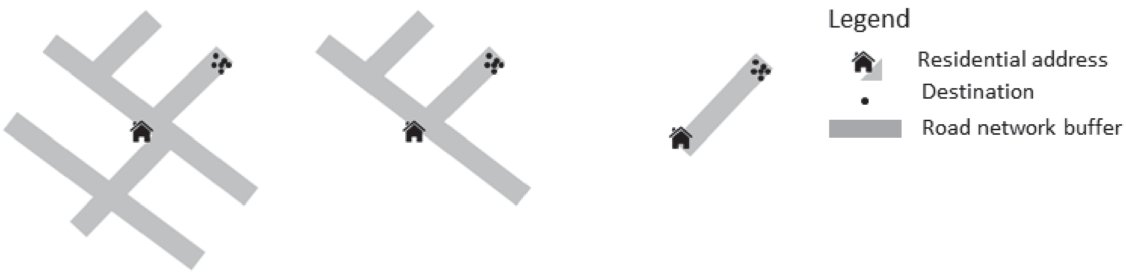


Figure 18. Additional road network buffer limitations – part 3.

While the examples in Figures 16-18 demonstrate limitations with the measurement of the built environment using road network buffers, these issues are also relevant to other types of delineation methods.

Another question is whether variation of the built environment within a buffer makes much difference. At smaller scales it is unlikely to make a difference, yet as scale increase the impact of these issues are likely greater.

Although measurement of spatial pattern is common in other fields, it is not often addressed in built environment and physical activity research. As illustrated above, spatial patterning is pertinent to both delineation of neighbourhood/exposure and methods of measuring the built environment. Built environment and physical activity researchers are starting to consider spatial patterning. For instance, Manaugh and Kreider (2013), have proposed a measure of mixed land use that accounts for the spatial mixing/interaction within an area of interest (as opposed to solely measuring proportions or counts of land use). Tribby et al. (2015) and Mayne et al. (2013) have used Moran's I – a measure of spatial patterning – in recent studies of walkability. Matthews and Yang (2013), have identified a similar issue whereby the absolute and relative location of neighbourhood boundaries are ignored in current analyses.

These issues demonstrate that, in the quest for greater precision in the measurement of context, it is also worth considering how delineation methods interact with a range of built environment measures and the pattern of the street network. It is possible that this unmeasured variation in the environment within the buffer may make it difficult to detect relationships between the environment and health.

6.4.1.7 Examples of limitations

Figure 19 illustrates several of the limitations discussed above using data from the KITC study. Figure 19a demonstrates that road network buffers around a residential address can exclude important places visited by the participant during data collection. Neither the 400 m nor the 800 m road network buffers capture the child's school environment, and both only capture a part of the child's journey to school. Additionally, both buffers exclude the majority of the home residential parcel. In this case, the child's home is located at the end of a long driveway that is further than 50 m from the road centreline.

Figure 19b shows part of the child's journey to school was along pedestrian only paths not included in the road network and, regardless of the distance used in the buffer, this part would never be included in the buffer. This issue was identified earlier in this chapter (Figure 15), where the road network buffer did not capture any GPS data points for one participant because the child did not visit roads in the immediate vicinity of their home. Instead, they travelled to and from home via a vacant lot accessible from the back of the residential property.

Figure 19. Examples of limitations of road network buffers.

Figure 19b also demonstrates how some built environment features may or may not be included in the buffer depending on how they are represented. For example, if the parks are represented as points instead of polygons, then their inclusion in the road network buffer can depend on where the point representing the park is placed (often an automated or arbitrary decision). As discussed in Chapter 3, this choice of how to represent the raw built environment data can alter the built environment measures calculated for each buffer.

Lastly, Figure 19b also shows that the road network buffer would better capture places the child visited if the home buffer was oriented towards the school and/or the school was included in the buffer. It is also worth noting that some activity appears to be centred around the school.

6.4.2 Limitations of analyses

There were a couple of limitations with the analyses undertaken in this chapter. First, due to missing GPS data, the method to estimate the spatial extent of where children went (i.e., the GPS daily path area) is a likely underestimation of where children spent time. Second, the GPS data came from only seven days of data collection. Therefore, the daily path areas used here may not be representative of the participant's usual behaviour.

6.5 Conclusion

Most studies that compare buffers only have the potential to draw conclusions about the relative size of buffers and whether they produce different built environment measures and different modelling results. They cannot state whether a certain buffer is better or worse at representing participants' mobility than any other buffer.

However, it is more important to know which delineations best represent a participant's exposure to the environment than it is to know which delineations produce the strongest associations. This chapter has presented new evidence on how well road network buffers represent where people travel and spend time, and has expanded the scope of this question by exploring the concepts of commission and omission errors.

The results showed that while the smallest buffer – the 400 m road network buffer - minimised the error in identifying the spatial extent of the places children travel, none of the road network buffers adequately capture the spatial extent of the places where children spend the most time.

This chapter has also identified six limitations in the use of road network buffers. While these limitations were identified based on data from a study of children, they are likely to be relevant to other populations. To date, most of these limitations have not been acknowledged in the literature. For those that have been identified previously, little attention has been given to evaluating their impact or addressing them in the context of improving road network buffers.

Explicitly acknowledging the limitations of road network buffers has a number of benefits. First, it allows researchers to understand and interpret results of studies that use road network buffers more accurately. For instance, an understanding of one of these limitations helped explain the unusual result discussed in this chapter, where participants recorded GPS points at home but not in their road network buffer. Second, it provides a basis for improving road network buffers. Finally, we can assess different delineation methods in terms of how well they address the road network buffer limitations.

Chapter 7. How well do activity space measures represent where children spend time?

7.1 Introduction

The previous chapter concluded that, for the children in the KITC study, road network buffers do not represent their exposure to the environment accurately. In the KITC dataset, on average, more than half of the spatial extent visited by children, and more than half of the time, captured by the seven-day GPS data were not captured by road network buffers.

However, road network buffers are not the only method of conceptualising and delineating neighbourhood boundaries. Activity spaces - spaces that people visit, travel through, and see in the course of their daily activities (Schönfelder and Axhausen 2003, Vallee et al. 2010) - were reviewed in Chapter 2. Briefly, there are number of common methods of calculating activity space: SDE, convex hull, and daily path areas. A few health researchers are developing new activity space delineation methods such as localised SDEs (Boruff et al. 2012), kernel density based methods (Thierry, Chaix and Kestens 2013), and oriented ellipses (Madsen et al. 2014).

All methods of delineating activity space at least partially address three of the limitations of road network buffers. First, by definition, activity spaces extend beyond the residential address, unlike road network buffers calculated solely around residential addresses. Second, delineations of activity spaces are centred on activity locations/destinations, not roads. Third, since activity spaces are based on where people visit and spend time, they implicitly address the mismatch between anisotropic movement and activity and isotropic road network buffers. For these reasons, activity space methods offer a promising alternative to road network buffers.

This chapter explores how well a range of methods of operationalising activity spaces perform in terms of representing where children spend time. It builds on existing activity space research by using KITC GPS data to create ten different representations of activity space, using a variety of methods. The activity space methods applied here include both common methods - standard deviation ellipse (SDE), convex hull, and daily path areas – and methods taken from the ecological literature – temporal localised convex hulls, and kernel density estimation.

Using the same approach as the previous chapter, a range of activity spaces are calculated. The different activity space delineation methods are then are compared to GPS data by calculating the overlap between activity spaces and GPS-based daily path areas, and by calculating the proportion of GPS data recorded within the activity spaces. The results of these analyses will provide insight into how well different activity spaces represent where children spent time.

7.2 Methods

7.2.1 Dataset

The subset GPS dataset – which contained 85 participants - was used for this analysis. See Chapter 5 for a description of how this dataset was created. As with the previous chapter, all analyses were undertaken with non-vehicle GPS data only. See Chapter 4 for a description of non-vehicle GPS data extraction.

7.2.2 Creation of activity spaces

Five different methods were used to create a total of ten different activity spaces using non-vehicle GPS points (Table 21).

Table 21. Activity spaces methods.

Activity space method	**Activity space (abbreviation)**
Minimum convex hull	Convex hull (CH)
Standard deviation ellipse	1-Standard deviation ellipse (SDE)
Daily path area	Daily path area (DPA)
Temporal localised convex hull	50% Temporal localised convex hull (TLCH50)
	75% Temporal localised convex hull (TLCH75)
	95% Temporal localised convex hull (TLCH95)
Kernel density estimation	Kernel density estimation – selecting areas/cells where a participant spent approximately 5 hours or more over the data collection period (KDE05)
	Kernel density estimation – selecting areas/cells where a participant spent approximately 7 hours or more over the data collection period (KDE07)
	Kernel density estimation – selecting areas/cells where a participant spent approximately 9 hours or more over the data collection period (KDE09)
	Kernel density estimation – selecting areas/cells where a participant spent approximately 12 hours or more over the data collection period (KDE12)

The minimum convex hull (CH) is the smallest convex polygon that encloses a set of points. Convex hulls were calculated for each participant using the 'Minimum Bounding Geometry' function in ArcGIS. The 1-standard deviation ellipse (SDE) is an ellipse that captures approximately two-thirds of the points and is centred on the mean centre. The 1-SDE was calculated for each participant using the ‘Directional Distribution function in ArcGIS. The daily path area (DPA) was calculated using processes documented in Chapter 6.

In contrast to a convex hull - which is created around all points – a temporal localised convex hull is created around each point and it’s *n* nearest neighbours in time and space (Getz et al. 2007). Temporal localised convex hulls were calculated using the ‘tlocoh’ package for R (Lyons, Turner and Getz 2013). T-LoCoH is a home range construction algorithm that adds a temporal dimension to the concept of localised convex hulls. GPS data were imported into R. The time-space scaling parameter (*s)* was set to 0.00001. This value was chosen to balance the time-space units and identify daily behaviour patterns, and is the recommended method in the T-LoCoH user manual (Lyons 2014).

An adaptive hull method was chosen due to the sparse nature of the GPS data. In this approach, neighbours are identified by their cumulative distance from their parent point. Neighbourhood identification occurs when the value of *a* is reached. In this analysis *a* was set to 500, which is the time-space distance between all points in the hull (i.e., neighbourhood boundary). This value was chosen by visually assessing the results of multiple values of *a*. Temporal localised convex hulls were created using the parameters above. 50%, 75%, and 95% isopleths were created for each hull and exported into GIS format. The three different temporal localised convex hull delineations were named TLCH50, TLCH75, and TLCH95, respectively.

The activity spaces based on kernel density estimates (KDE) were created in ArcGIS using the kernel density function. The cell-size was set to 5 m and the kernel was set to 50 m to align with the daily path area buffer distance. Four KDE-based activity spaces were created by selecting cells that met the following criteria and then converting those cells to polygons:

- KDE05 – only those cells with densities greater than or equal to 0.24 GPS points/m^2 are included in the activity space. This density approximates a total of 5 hours or more of time spent in these cells over the data collection period. Since a GPS point is recorded every 30 s, 600 GPS points comprise 5 hours of time. The area of interest is 50 m x 50 m, which is 2,500 m^2. Therefore, the cut-off density is 600 GPS points divided by 2,500 m^2 = 0.24 GPS points/m^2.

- KDE07 – only those cells with densities greater than or equal to 0.336 GPS points/m^2. This density approximates a total of 7 hours or more of time spent in these cells over the data collection period.

- KDE09 – only those cells with densities greater than or equal to 0.432 GPS points/m^2. This density approximates a total of 9 hours or more of time spent in these cells over the data collection period.

- KDE12 – only those cells with densities greater than or equal to 0.576 GPS points/m^2. This density approximates a total of 12 hours or more of time spent in these cells over the data collection period.

Figure 20 is a map of a single participant's daily path area overlaid with three road network buffers (400, 800, 1600 m) and the ten activity spaces calculated in this analysis. Figure 21 shows the same map for a different participant. The participants in the two figures were chosen to illustrate diverse travel patterns and activity spaces, with the Figure 20 participant having more constrained travel, and consequently smaller activity spaces than the participant in Figure 21 (note the different scales on the maps).

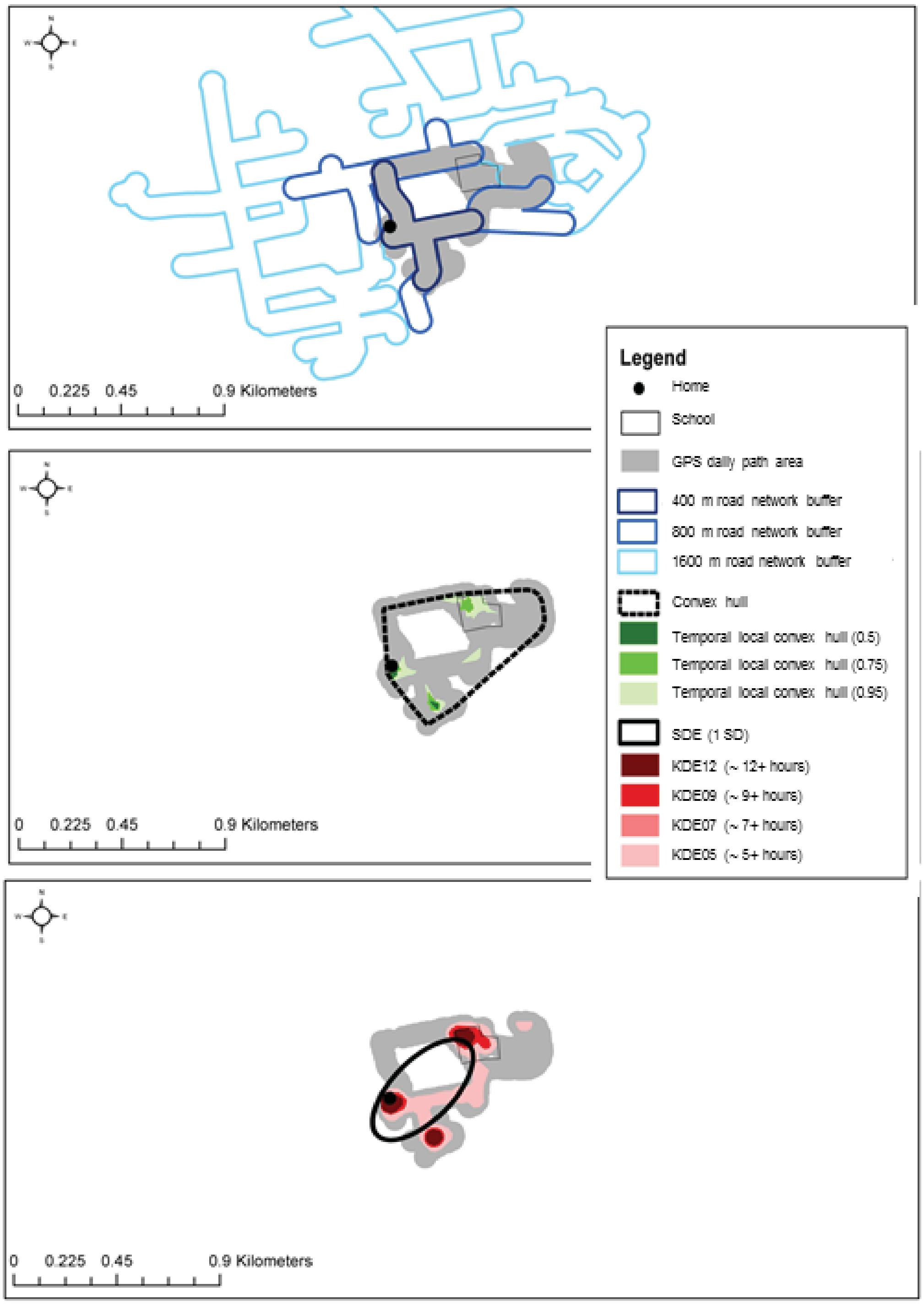


Figure 20. Example buffers and activity spaces for a single participant compared to the 50 m GPS buffer daily path area: a) road network buffers at 400, 800, 1600 m, b) convex hull based activity spaces (CH, TLCH50, TLCH75, TCH95), and c) activity spaces (SDE, KDE12, KDE09, KDE07, KDE05)

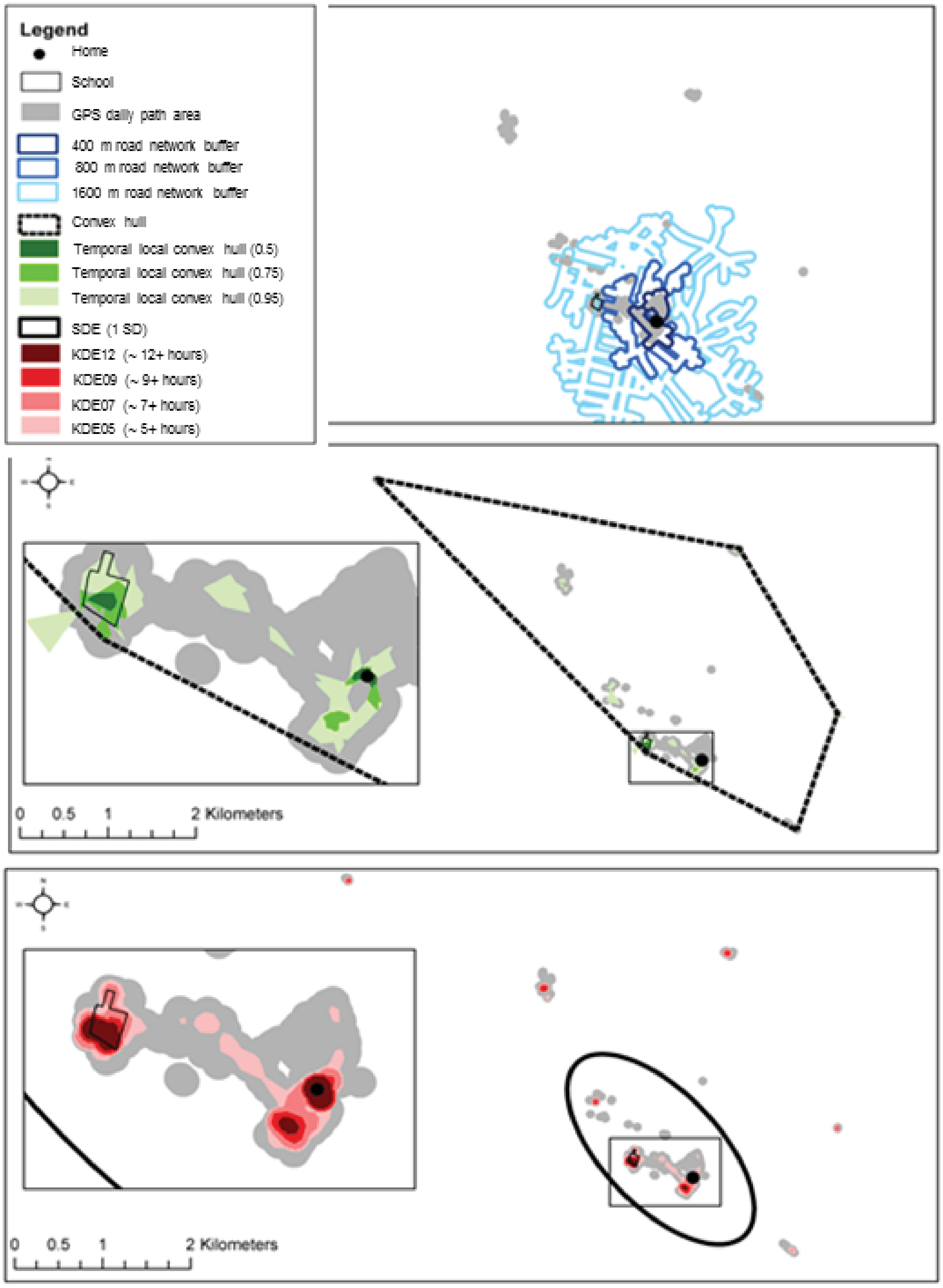


Figure 21. Example buffers and activity spaces for a single participant compared to the 50 m GPS daily path area: a) road network buffers at 400, 800, 1600 m, b) convex hull based activity spaces (CH, TLCH50, TLCH75, TCH95), and c) activity spaces (SDE, KDE12, KDE09, KDE07, KDE05)

7.2.3 Comparing GPS data and activity spaces

The following comparison measures were calculated to compare the activity space delineations: overlap area, commission error area, omission error area, percentage of the activity space overlapped by the daily path area, percentage of the daily path area overlapped by the activity space, total error area, total hours GPS data captured by the activity space, and percentage of GPS data captured by the activity space. The methods used to calculate these measures were described in Chapter 6.

The following composite measures were also calculated, to enable comparison with the 400 m road network buffer (which was shown to be the best road network buffer in Chapter 6): additional total error area, additional total overlap area, and the difference between the additional overlap and additional error. For example, the additional total error area for the convex hull activity space is the total error of the convex hull minus the total error of the 400 m road network buffer. Similarly, the additional total overlap area is the total overlap area of the convex hull minus the total overlap area of the 400 m road network buffer. The difference between the additional overlap and additional error is the additional total overlap area minus the additional total error area. A positive difference indicates that the activity space in question adds more overlap than it does error, and, therefore, improves on the 400 m road network buffer.

7.2.4 Statistical analysis

Paired bivariate analyses using non-parametric Wilcoxon tests ($\alpha = 5\%$) compared the daily path areas with each of the different activity spaces. Statistical analyses were conducted in *R* (R Development Core Team 2008).

7.3 Results

Table 22 presents descriptive statistics for the areas of the ten different delineations of activity space. In this analysis, the GPS daily paths represent the places children went during the seven-day GPS data collection, whereas the other activity space delineations are alternate representations of children's exposure to the environment. The daily path was significantly larger, on average, than the temporal localised convex hulls and the kernel density activity spaces. Conversely, the daily path was significantly smaller, on average, than both the convex hull and standard deviation ellipse. As previously illustrated in Figure 20 and Figure 21, the activity spaces delineated by convex hulls and standard deviation ellipses are orders of magnitude larger than not only the other activity spaces but also the road network buffers from the previous chapter (range 0.14 – 3.85 km^2; Table 17).

Table 22. Descriptive statistics of the areas (km^2) of GPS daily path areas and different activity spaces. Subset GPS dataset (*n* = 85).

	Mean	Median	SD
GPS daily path	0.630	0.510	0.410
CH	49.130	16.250	106.960
SDE	23.160	3.170	77.440
TLCH50	0.005	0.004	0.004
TLCH75	0.020	0.010	0.020
TLCH95	0.150	0.090	0.180
KDE05	0.110	0.110	0.040
KDE07	0.060	0.060	0.020
KDE09	0.030	0.030	0.010
KDE12	0.020	0.020	0.000

Table 23 presents results from the overlap analyses, comparing each of the activity space measures with the GPS daily path area. All activity spaces were calculated using GPS data and many of the methods are based on inclusion of a certain percentage of GPS points. For instance, the convex hull necessarily includes all GPS points. Therefore, all results should be interpreted with this in mind.

While the omission error is practically zero for the convex hull, it also has the highest commission error. Contrast this to the KDE-based activity spaces which have low errors of omission and commission. The convex hull also has a very low percentage activity space overlap. In other words, on average, only 7.6% of the convex hull is covered by the daily path. In comparison, most of the temporal localised convex hulls and the KDE activity spaces are almost completely covered by the daily path (percentage activity space overlap).

Table 24 presents composite measures of overlap between the activity spaces and the daily path area. The table also presents comparisons with the 400 m road network buffer. For instance, the convex hull activity spaces added on average an additional 47.95 km^2 of total error area and an additional 0.5 km^2 of overlap area than the 400 m road network buffer. The column 'Additional overlap – additional error' is the additional total error subtracted from the additional overlap. Positive values indicate that a particular activity space performed better than the 400 m road network buffer, as it added more overlap than error.

Table 23. Comparing the spatial extent of GPS daily paths with activity spaces: overlap and errors of commission and omission. Subset GPS dataset ($n = 85$).

Activity space	Overlap area (km^2)			Commission error area (km^2)			Omission error area (km^2)			Percentage activity space overlap			Percentage daily path area overlap		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
CH	0.57	0.45	0.40	48.55	15.79	106.88	0.01	0.01	0.01	7.60	3.50	13.10	88.70	90.50	6.30
SDE	0.36	0.30	0.26	21.63	1.61	78.17	0.23	0.19	0.16	16.30	7.50	20.20	56.80	56.90	16.50
TLCH50	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.51	0.41	99.70	100.00	2.10	0.80	0.70	0.60
TLCH75	0.02	0.01	0.02	0.00	0.00	0.01	0.61	0.51	0.40	98.60	100.00	5.60	2.80	2.40	1.80
TLCH95	0.11	0.08	0.10	0.04	0.00	0.10	0.51	0.45	0.32	89.30	95.70	14.80	16.70	15.70	6.30
KDE05	0.10	0.10	0.04	0.00	0.00	0.01	0.02	0.01	0.03	98.80	100.00	10.80	19.50	19.10	6.90
KDE07	0.06	0.06	0.02	0.00	0.00	0.00	0.03	0.02	0.04	100.00	100.00	0.00	11.40	10.30	4.50
KDE09	0.03	0.03	0.01	0.00	0.00	0.00	0.03	0.02	0.04	100.00	100.00	0.00	5.80	5.10	2.70
KDE12	0.02	0.02	0.00	0.00	0.00	0.00	0.03	0.02	0.04	100.00	100.00	0.00	3.40	2.90	1.70

Table 24. Composite measures of activity space overlap with daily path areas. Subset GPS dataset (n = 85).

	Mean overlap area (km^2)	**Mean total error area (km^2)**	**Additional overlap area (km^2)***	**Additional total error area (km^2)***	**Additional Overlap -additional error***
400 m road network buffer*	0.07	0.62	-	-	-
CH	0.57	48.57	0.5	47.95	-47.45
SDE	0.36	21.86	0.29	21.24	-20.95
TLCH50	0.00	0.62	-0.07	0	-0.07
TLCH75	0.02	0.61	-0.05	-0.01	-0.04
TLCH95	0.11	0.55	0.04	-0.07	0.11
KDE05	0.10	0.03	0.03	-0.59	**0.62**
KDE07	0.06	0.03	-0.01	-0.59	0.58
KDE09	0.03	0.03	-0.04	-0.59	0.55
KDE12	0.02	0.03	-0.05	-0.59	0.54

Based on these composite measures, the following activity spaces performed better than the 400 m road network buffer in terms of increasing overlap and minimising errors of commission and omission: TLCH95, KDE05, LDE07, KDE09, KDE12.

Table 25 presents the hours and percentage of non-vehicle GPS data recorded within the activity spaces. Results for the convex hull activity space are not listed in the table since by definition the convex hull includes 100% of GPS points. Aside from the convex hull, the activity space measures that capture the most GPS data are the TLCH95 and the KDE05 activity space delineations. This is not surprising since the temporal local convex hull and KDE activity space boundaries were delineated based on the hours/percentage of GPS points included in the activity space. All activity space delineations captured a greater percentage of GPS data than the road network buffers analysed in Chapter 6 (mean % GPS points captured by road network buffers ranged from 34.8 – 48.4 %; Table 17). Again, this is not surprising since the activity space delineations were created using the GPS data and the road network buffers were created independent of the GPS data.

7.4 Discussion and conclusion

In addition to the daily path area previously calculated in Chapter 6, this chapter presented nine additional delineations of activity spaces. In a comparison with the 400 m road network buffer, many of the activity spaces did a better job of maximising overlap with the daily path and minimising error areas. The KDE05 activity space performed the best as it maximised additional overlap in comparison to the additional error added.

It is worth noting that two commonly used activity space methods – the convex hull and SDE – were not as effective at representing children's mobility and minimising errors of commission as the other methods presented here. Therefore, if researchers intend to use activity spaces as proxies of exposure to the environment, they should consider using more sophisticated delineation methods, such as the spatio-temporal KDE approaches developed in Geographic Information Science (e.g., Demšar and Virrantaus 2010, Nakaya and Yano 2010). Moreover, there may be potential to borrow from ecology and draw on advanced 'home range' delineation methods. For instance, Scull et al. (2012) have used local convex hulls to estimate the home range of Ugandan mountain gorilla, Stein et al. (2011) have used kernel density estimates to estimate the home range of leopards in Namibia, and Dürr and Ward (2014) have used temporal localised convex hulls and biased random bridge methods to delineate the home ranges of domestic dogs in Australia.

Unlike the road network buffers, all these activity spaces were calculated using GPS data. This means that the activity space delineation methods presented here are only possible if GPS or similar data – such as geocoded travel survey, travel diary data, or mobile phone records – are available. The collection of GPS data is expensive and not feasible for many research studies. Therefore, even though many of the activity spaces we examined performed better than the best road network buffer, there is still a need for better neighbourhood delineations that do not require GPS data. Therefore, the next chapter will explore how road network buffers can be improved, so as to better represent exposure to the environment.

Table 25. Hours and percentage of non-vehicle GPS data recorded within the activity spaces. Subset GPS dataset (*n*= 85).

	Hours of GPS data in Activity Space					% GPS points in Activity Space				
	Min	**Max**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Mean**	**Median**	**SD**
SDE	11.7	58.5	38.6	38.0	9.9	54.4	99.3	86.5	89.8	10.9
TLCH50	10.5	41.9	27.3	27.3	6.4	52.3	81.9	61.3	60.1	6.0
TLCH75	14.3	52.5	36.6	36.5	8.5	76.6	97.9	82.1	81.5	3.4
TLCH95	16.6	64.1	43.6	43.7	10.0	94.7	99.6	97.5	97.6	1.3
KDE05	16.7	62.9	43.3	44.8	9.8	90.7	99.6	97.1	97.2	1.7
KDE07	16.6	60.7	42.0	42.1	9.5	83.7	98.7	94.0	94.5	3.0
KDE09	15.8	55.9	39.4	40.3	9.0	73.8	96.2	88.4	89.2	5.2
KDE12	13.9	52.6	36.0	34.8	8.8	59.3	93.2	80.7	81.3	7.7

Chapter 8. Home, school and in between: enhancing road network buffer to better represent neighbourhoods and exposure

8.1 Introduction

This dissertation has already established that road network buffers tend to be a better choice than administrative and Euclidean buffers when delineating boundaries that represent exposure to the built environment (Chapter 3). Therefore, Chapter 6 investigated the degree to which road network buffers - at a range of scales - captured children's exposure to the environment. While the 400 m road network buffer was identified as the buffer that minimised errors of omission and commission, none of the road network buffers were good representations of actual exposure to the environment. In the KITC dataset, on average, more than half of the spatial extent visited by children and more than half of the time captured by the seven-day GPS data was not captured by road network buffers.

Consequently, Chapter 7 moved beyond road network buffers and implemented a range of activity space delineations, concluding that the KDE05 delineation best represented children's mobility while minimising errors of commission. Chapter 7 also found that many activity space representations performed better than the 400 m road network buffer.

These analyses would seem to suggest that activity spaces are the ideal type of delineation method for researchers to use when representing exposure. However, the activity space representations implemented in the previous chapter all require detailed location data (e.g., GPS, travel survey), but this kind of data is not always available, and can be too expensive and/or intrusive to collect in practice. Therefore, there is a need to develop better delineations of exposure to the environment that do not require detailed location data.

In theory, it ought to be possible to use knowledge about key locations in people's lives to create better delineations. This chapter explores this idea by enhancing and modifying the standard road network buffer to: a) better assess potential access and b) better estimate exposure to the built environment. First, building on the limitations of road network buffers identified in Chapter 6, five methods of enhancing the standard network buffer to better capture exposure to the environment are proposed. Next, one of these methods is operationalised using the KITC data and compared to the GPS data. Finally, the results are presented and discussed.

8.2 Potential enhancements to the standard road network buffers

The purpose of these enhancements is to create road network buffers that better represent the neighbourhood and exposure to the environment. Five potential methods of improving road network buffers were identified, and are listed below.

1. **Inclusion of common destinations.**

   Create a road network buffer around home and a road network buffer around other frequently visited locations, such as the second places of work/school and 'third place' destinations (Carroll et al, 2015). These buffers can then be combined into a single buffer.

2. **Inclusion of transitory spaces (e.g., pedestrian paths).**

   Use a network of transitory third places such as roads and pedestrian paths to create an enhanced buffer.

3. **Inclusion of private and public spaces along the road network.**

   Supplement the road network buffer, either with polygons of land parcels of frequently visited locations, or with all land parcels that intersect the road network buffer.

4. **Varying the orientation of the buffer.**

   Orient the buffer towards frequently visited locations, such as work and school.

5. **Varying the shape (width and length) of the buffer.**

   Vary the shape of the buffer based on additional information, such as road infrastructure (e.g., traffic lights, number of lanes), traffic speed/volume, pedestrian infrastructure (e.g., footpaths, pedestrian crossings), and topography/slope.

The development, implementation, and testing of all five potential enhancements is beyond the scope of this dissertation. Therefore, this dissertation will concentrate on only the first enhancement, the inclusion of common locations in addition to the home. As before, the enhanced road network buffers will be assessed by comparing them with GPS daily path areas, representing the places children visited during the seven-day GPS data collection.

8.3 Methods

8.3.1 Data

Data collection and GPS data processing were described earlier, in Chapters 4 and 5. All analyses in this section were conducted for the GPS dataset with inclusion criteria applied (*n*= 85). The remainder of this section describes the methods used to create enhanced road network buffers, create polygon representations of the GPS data, and compare the road network buffers with the GPS data.

8.3.2 Buffer creation

The first step required to create the enhanced road network buffers was to identify destinations to create additional road network buffers around. Not surprisingly, travel diary data indicated that, after home, the most common destination for the children in the KITC study was school, with an average of just under five trips during the seven day data collection period (Carroll et al. 2015). The next most common destination visited by children was 'shops', with on average 2.7 – 4.7 trips - for inner city and suburban children, respectively - undertaken in the seven-day data collection period (Carroll et al. 2015).

'School' was included as another destination to create road network buffers around. While shops were another frequently visited destination that could be included, the decision was made to restrict the enhanced buffers to only one additional destination so as to isolate the effects of an additional destination.

Next, road network buffers at a range of scales were created around both home and school. Scales of 400, 600, and 800 m were chosen, since the work carried out in Chapter 6 had demonstrated these smaller buffers minimised the total error area and maximised the sum of the percentage overlap. Six versions of the enhanced road network buffers, representing a range of scale combinations were calculated (Table 26). Since children spend more time at home than at school, the size of the school road network buffer was always less than or equal to the size of the home road network buffer.

Table 26. Enhanced road network buffer scale combinations.

Scale combination	Home scale (m)	School scale (m)
1	400	400
2	600	400
3	600	600
4	800	400
5	800	600
6	800	800

Access to schools is more realistically modelled using school entrance locations (Harrison et al. 2014) than a single centroid. Therefore, school entrances were identified on Google Maps and digitised. Road network buffers were calculated around each school entrance. Once this was done, the home and school buffers were merged for each participant (e.g., Figure 22.)

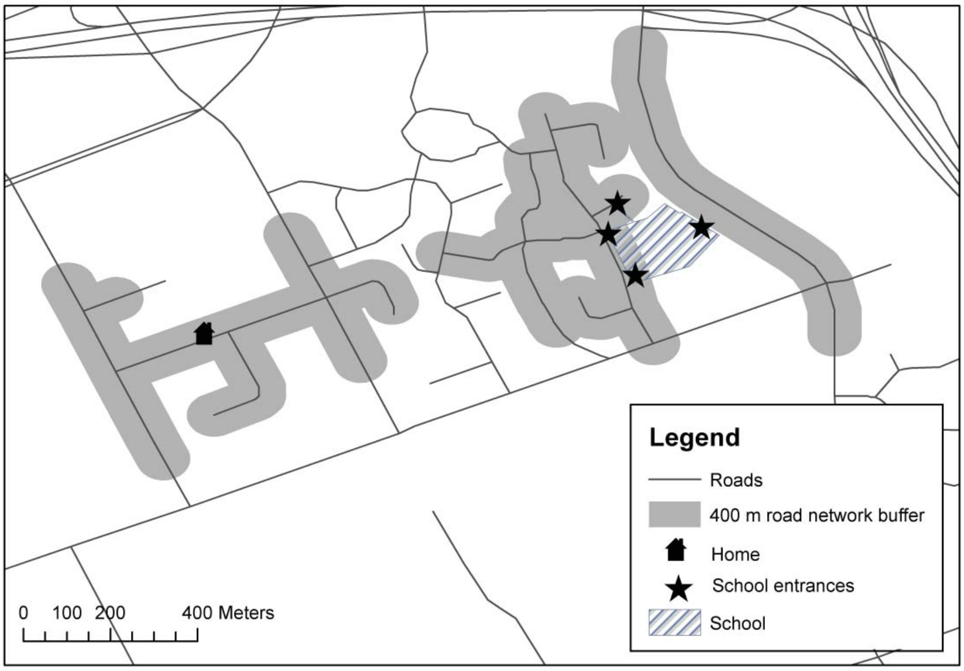


Figure 22. Example enhanced road network buffer.

8.3.3 Comparing the GPS data and enhanced road network buffers

The enhanced road network buffers were compared with GPS daily path areas. The seven measures of geographical overlap described in Chapter 6 were calculated for each buffer. Briefly, these measures were: area of overlap; area of commission error; area of omission error; percentage of road network buffer overlapped by daily path area; percentage of daily path area overlapped by road network buffer; and the total number and total percentage of GPS points within the road network buffers.

The three composite measures employed in Chapter 7 were also calculated: additional total error area, additional total overlap area, and the difference between the additional overlap and the additional error.

8.3.4 Statistical analyses

Descriptive statistics were calculated for the enhanced road network buffers. Paired bivariate analyses using non-parametric Wilcoxon tests ($\alpha = 5\%$) compared the daily path areas with each of the enhanced road network buffers. Statistical analyses were conducted in *R* (R Development Core Team 2008).

8.4 Results

Table 27 presents results of the overlap analysis comparing daily path areas with the enhanced road network buffers at a range of scales. For comparison purposes, results from the 400, 600, and 800 m road network buffers (from Chapter 6) are included in the first three rows.

The results shown in Table 27 are consistent with what was expected. Namely, adding in road network boundaries around schools increased the overlap, increased the commission error and decreased the omission error. As with the results presented in Chapter 6, the magnitude of the commission error was much larger than the magnitude of the omission error, which means that with every increase in scale the total error also increased.

Table 28 presents results from the composite measures of buffer overlap for the standard road network buffers created around residential addresses (Chapter 6), the activity space delineations (Chapter 7), and the enhanced road network buffers created around residential addresses and schools. The additional overlap and total error areas given are in comparison with the standard 400 m road network buffer. For example, when moving from a standard 400 m road network buffer to a standard 600 m road network buffer an additional 0.05 km^2 of overlap area was added and an additional 0.09 km^2 of error area was added on average. For the 600 m road network buffer, the ratio of the additional overlap area to additional error area was 0.56.

The bottom section of Table 28 presents composite measures for the enhanced road network buffers created around residential addresses and schools. Results suggest that, the enhanced road network buffer created at a 400 m distance around both home and school improves on the standard 400 m road network buffer since the difference between additional overlap and additional error is positive.

The results also demonstrate that, in general, enhancing the road network buffers by adding in the school location provided a better representation of exposure than simply increasing the scale of the standard road network buffers. For instance, moving from a standard 400 m road network buffer to a standard 1000 m road network buffer yielded a difference of -0.44 (i.e., the difference between additional overlap area and additional error area). In contrast, moving from a standard 400 m road network buffer to an enhanced road network buffer (600 m around home and 400 m around school) yielded a greater difference -0.05.

While all enhanced road network buffers were an improvement on the convex hull activity space, they did not perform as well as the majority of the activity space delineations. However, this was expected since the activity space delineations were created using the same GPS data that they were subsequently compared to (i.e., daily path area).

Table 27. Comparison of the spatial extent of GPS daily paths with enhanced road network buffers: overlap and errors of commission and omission. Subset GPS dataset (n = 85).

			Overlap			**Commission error**			**Omission error**		**Percentage RNB overlap**			**Percentage daily path area overlap**			**Total error**	
Buffer	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**	**Mean**	**Median**	**SD**
Standard road network buffers																		
400 m	0.07	0.06	0.05	0.07	0.07	0.04	0.55	0.44	0.39	50.7	48.8	24.2	14.0	11.8	8.6	0.62	0.52	0.39
600 m	0.12	0.10	0.08	0.20	0.19	0.1	0.51	0.39	0.38	35.8	33.7	20.0	21.1	19.9	13.1	0.71	0.64	0.38
800 m	0.16	0.12	0.12	0.43	0.42	0.19	0.47	0.36	0.37	26.3	24.3	16.7	27.9	23.8	17.6	0.90	0.87	0.4
Enhanced road network buffers																		
Home 400 m School 400 m	0.16	0.15	0.07	0.24	0.24	0.06	0.46	0.34	0.38	39.5	39.0	12.8	30.9	30.1	13.5	0.70	0.60	0.37
Home 600 m School 400 m	0.19	0.17	0.10	0.36	0.36	0.11	0.43	0.32	0.361	33.8	32.9	12.4	35.1	32.9	15.0	0.79	0.70	0.37
Home 600 m School 600 m	0.22	0.19	0.11	0.57	0.56	0.14	0.41	0.29	0.35	27.0	26.4	10.3	39.1	41.4	15.9	0.97	0.91	0.38
Home 800 m School 400 m	0.21	0.19	0.13	0.56	0.56	0.19	0.41	0.28	0.35	27.0	24.7	11.2	38.6	38.6	16.4	0.97	0.91	0.38
Home 800 m School 600 m	0.24	0.19	0.15	0.75	0.76	0.22	0.38	0.27	0.34	23.4	22.5	9.7	41.9	44.3	17.0	1.13	1.10	0.40
Home 800 m School 800 m	0.26	0.22	0.16	1.04	1.06	0.28	0.36	0.25	0.33	19.2	18.2	8.3	44.4	46.5	17.3	1.40	1.37	0.45

Table 28. Composite measures of road network buffer, activity space, and enhanced road network buffer overlap with daily path areas. Subset GPS dataset (n = 85).

Buffer	Mean overlap area (km^2)	Mean total error (km^2) area	Additional overlap area (km^2)*	Additional total error area (km^2)*	Additional Overlap - additional error *	Mean % GPS points in buffer	Additional % GPS points in buffer
Standard road network buffers created around residential addresses							
400 m*	0.07	0.62	-	-	-	34.8	-
600 m	0.12	0.71	0.05	0.09	-0.04	38.4	3.6
800 m	0.16	0.90	0.09	0.28	-0.19	40.6	5.8
1000 m	0.19	1.18	0.12	0.56	-0.44	42.5	7.7
1200 m	0.22	1.55	0.15	0.93	-0.78	43.8	9
1400 m	0.24	2.02	0.17	1.4	-1.23	45.5	10.7
1600 m	0.25	2.57	0.18	1.95	-1.77	46.6	11.8
1800 m	0.27	3.18	0.20	2.56	-2.36	48.0	13.2
2000 m	0.28	3.90	0.21	3.28	-3.07	48.4	13.6
Activity space							
CH	0.57	48.56	0.5	47.94	-20.74	100	65.2
SDE	0.36	21.86	0.29	21.24	0.29	86.5	51.7
TLCH50	0.00	0.62	-0.07	0	-0.06	61.3	26.5
TLCH75	0.02	0.61	-0.05	-0.01	0.02	82.1	47.3
TLCH95	0.11	0.55	0.04	-0.07	0.64	97.5	62.7

KDE05	0.10	0.02	0.03	-0.6	0.62	97.1	62.3
KDE07	0.06	0.03	-0.01	-0.59	0.58	94.0	59.2
KDE09	0.03	0.03	-0.04	-0.59	0.55	88.4	53.6
KDE12	0.02	0.03	-0.05	-0.59	-0.05	80.7	45.9
Enhanced road network buffers created around residential addresses and schools							
Home 400 m School 400 m	0.16	0.70	0.09	0.08	**0.01**	47.2	12.4
Home 600 m School 400 m	0.19	0.79	0.12	0.17	-0.05	47.2	12.4
Home 600 m School 600 m	0.22	0.97	0.15	0.35	-0.2	49.0	14.2
Home 800 m School 400 m	0.21	0.97	0.14	0.35	-0.21	49.4	14.6
Home 800 m School 600 m	0.24	1.13	0.17	0.51	-0.34	49.4	14.6
Home 800 m School 800 m	0.26	1.4	0.19	0.78	-0.59	49.8	15.0

*All additional areas of overlap and error were compared to the standard 400 m road network buffer.

8.5 Discussion

Five enhancements to road network buffers, which have the potential to improve the representation of the environment, have been proposed. This chapter has implemented the first proposed enhancement (combined home-school road network buffers) at a number of different scales. The degree to which the enhanced buffers represented exposure was assessed by comparing the buffers with GPS data. While a small number of researchers have begun incorporating buffers around non-residential destinations, this is the first research to test the extent to which the representation of both the spatial extent and time spent in the buffers is improved.

Results showed that, on average, the enhanced road network buffer (400 m around home and 400 m around school) was an improvement on the standard 400 m road network buffer. Furthermore, results suggested that enhancing road network buffers by including buffers around school produced better representations of children's exposure to the environment than simply increasing the scale of road network buffers centred around home.

The remaining proposed enhancements to road network buffers were not tested in this dissertation due to scope limitations. However, the potential of each of these four enhancements will now briefly be discussed.

The second proposed enhancement - inclusion of pedestrian paths - would allow for better representation of true mobility. The KITC data demonstrated that children were travelling along pathways not included in the road dataset. Therefore, pedestrian paths may be particularly important for representing children's potential and actual exposure to the environment. However, there are two key challenges when developing pedestrian enhanced network buffers. The first of these is obtaining pedestrian path data (Kang et al. 2015, Giles-Corti et al. 2014), and the second concerns the methodological challenges associated with representing footpaths in a GIS network (Tal and Handy 2012, Kang et al. 2015). Research is underway to address these issues (Kang et al. 2015, Senlet and Elgammal 2012, Smith et al. 2013), but it may be some time before pedestrian path data are widely available and standard methods, enabling researchers to easily use these data in the creation of pedestrian network buffers, are established.

The third proposed enhancement is the inclusion of private and public spaces along the road network. This enhancement – addresses the limitation that road network buffers are necessarily centred on roads One method of implementing this enhancement would be to merge all land parcels that intersect the road network buffer with the road network buffer. However, depending on the size of the dataset and the scale of the buffers, this process could be significantly more computationally intensive than calculating standard road network buffers. An alternative is to merge only the land parcels of key destinations such as home, school, and work. Based on an exploration of the KITC dataset, even including just the home and school parcels could substantially improve the amount of actual activity captured by road network buffers.

The fourth proposed enhancement – varying the orientation of the buffer – is perhaps more challenging to implement than the other proposed enhancements. Standard road network buffers can be considered anisotropic (i.e., oriented; Crawford et al. 2014), since they are determined by the presence/absence of a road network and - in most cases - roads do not radiate equally in all directions. However, road network buffers can also be considered isotropic, in the sense that - in most implementations - every road and every direction has equal importance. In other words, road network buffers spread out equally in all directions where roads exist.

Varying the orientation of a road network buffer – that is, explicitly weighting the buffer towards a certain direction – is a little more difficult to implement in practice. Standard GIS software does not provide oriented road network buffer functionality. A number of researchers have experimented with oriented buffers by buffering the shortest route between two points to create a version of oriented road network buffers (Boruff et al. 2012, Madsen et al. 2014, Harrison et al. 2014). While this approach automatically orients the buffer towards different destinations, there are a couple of limitations. First, this method focuses on the journey/travel component of activity. Second, relying only on the shortest route excludes all other possible routes. Preliminary research has demonstrated that the shortest routes as measured by GIS do not match actual routes as indicated by GPS data for children's journeys to school (Harrison et al. 2014, Duncan and Mummery 2007, Buliung et al. 2013), adult's commute routes (Badland et al. 2010, Dalton et al. 2015), and cycling routes (Krenn et al. 2014).

Madsen et al. (2014) implemented an oriented ellipse based on home and CBD locations. However, this ellipse suffers from the limitation of convex hulls and SDEs, namely that they include large areas that participants do not visit. Building on Madsen et al.'s oriented ellipses (Madsen et al. 2014), and overcoming the problem of buffers based on shortest routes, the following process to create oriented road network buffers is proposed. First, road network buffers are created around destinations of interest (e.g., home and school) that have been identified as relevant to each participant (Figure 23). This is the same step undertaken for the first proposed enhancement implemented in this chapter.

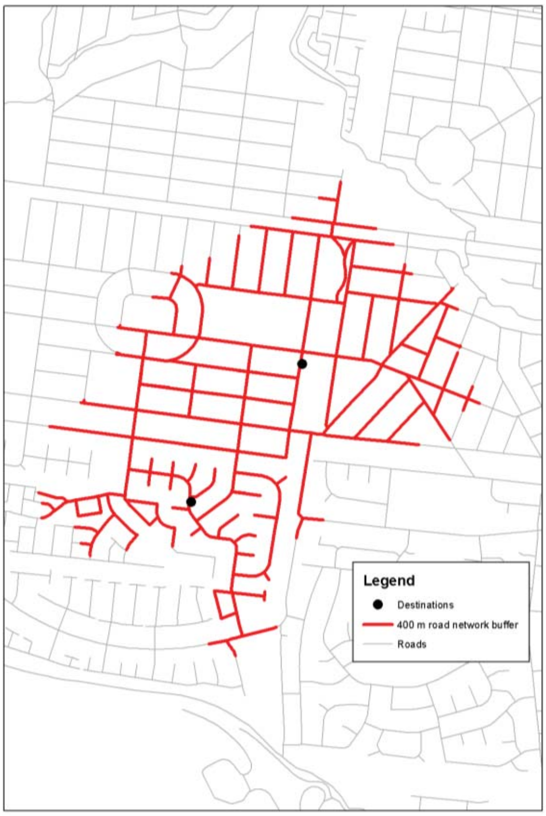


Figure 23. Implementing an oriented road network buffer step 1/3.

Next, a line is created between the two destinations (Figure 24). This line represents the orientation of the buffer.

Figure 24. Implementing an oriented road network buffer step 2/3.

Finally, the road network buffers within a certain distance of the linking line (200 m in this example) are selected as the oriented road network buffers (Figure 25).

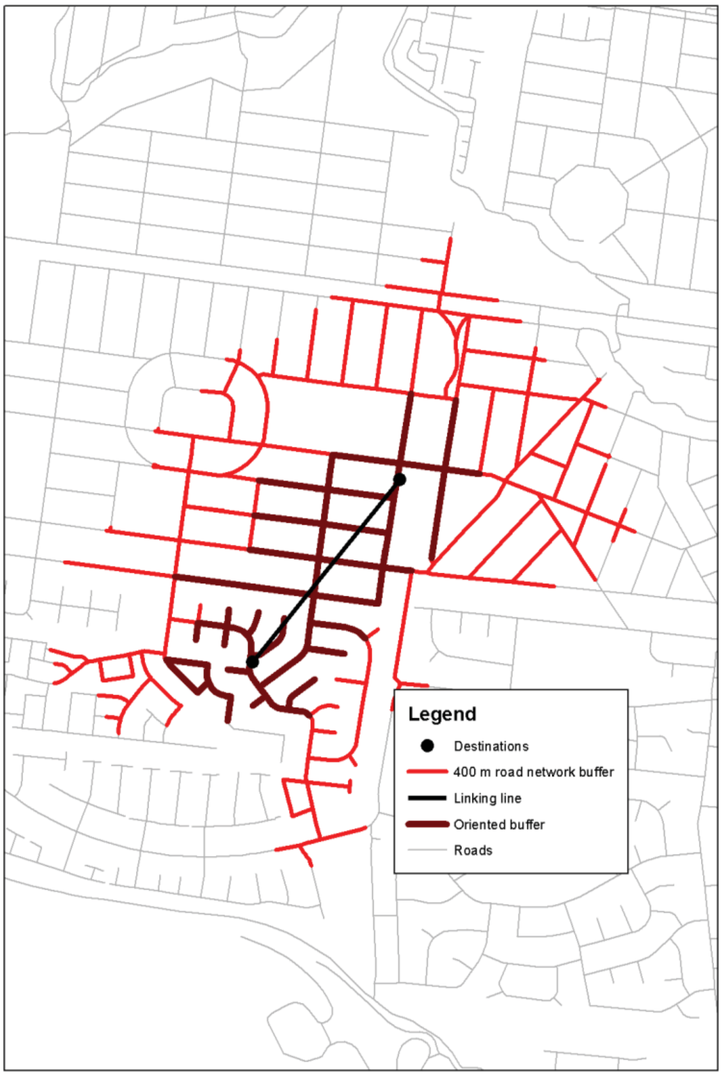


Figure 25. Implementing an oriented road network buffer part 3/3.

The fifth, and final, proposed enhancement is to vary the size and shape of the road network buffer based on characteristics of the environment that might influence movement (i.e., costs and barriers in GIS terminology). The concept behind this enhancement is that some routes are arguably faster, more pleasant and easier to travel along due to various route characteristics such as speed limit, pedestrian crossings, slope, safety from crime, and so on. In most cases incorporating these route characteristics would require a shift from road network buffers based on distance to those based on different costs (e.g., travel time, aesthetic costs).

Adding costs and barriers to a road network buffer is a relatively straightforward task to implement in ArcGIS. The challenge in this proposed enhancement lies in sourcing data that describes the additional route characteristics. Perhaps this is the reason that so few researchers have created buffers or routes enhanced by route characteristics. Of those that have incorporated costs and barriers, Bejleri et al. (2011) took a vector approach by including costs and barriers in the network, whereas others have used a raster cost-surface approach to create more refined measures of accessibility (Ray and Ebener 2008, Boruff et al. 2012).

8.6 Conclusion

As demonstrated in Chapter 6, road network buffers captured less than half of children's activity and mobility. This means that using road network buffers to represent exposure to the environment is likely to exclude much of the environment that participants are actually exposed to. While road network buffers do better at representing potential exposure to the environment than delineation methods such as Euclidean buffers or administrative units, there are ways that road network buffers could be enhanced.

The five potential approaches to enhancing/modifying road network buffers presented in this chapter could provide researchers with a better representation of both potential and actual exposure. This was demonstrated by implementing one of the suggested enhancements – the addition of school-based buffers – and comparing its performance with standard road network buffers. In general, the enhanced buffer did a better job of minimising errors and maximising GPS points captured.

Although space considerations prevented a full implementation of the other proposed enhancements, a brief discussion of how these could be carried out was provided. As many of these enhancements can be implemented simply with only a little additional information, future work should test a range of these enhancements.

Chapter 9. Discussion and conclusions

9.1 Summary of findings

This dissertation has addressed the challenge of developing a more precise delineation of neighbourhood and exposure to the environment by systematically comparing a number of GIS-based delineation methods at a range of scales.

Chapter 2 reviewed delineation methods in common use and compared these methods. It demonstrated that there are numerous existing delineation methods, and the choice of method and scale can make a difference to research results. The review of the literature identified three gaps that this dissertation subsequently addressed. The first of these gaps was the lack of clarity around which delineation methods and scales are most appropriate to use in specific circumstances. The second was the lack of evidence on how well different delineation methods capture exposure to the environment. The third, and final, gap was the need for delineation methods that better capture exposure, yet are not reliant on detailed mobility data such as GPS data.

Chapter 3 compared the results of models of the associations between the built environment and physical activity. The built environment was measured within a number of different residential neighbourhoods using data from the URBAN study. Results echoed the existing literature by demonstrating that choice of neighbourhood delineation method, scale, built environment measure, and physical activity measure all determined whether a statistically significant association was found between the built environment and physical activity. The choice of buffering algorithm only made a meaningful difference for one built environment measure; the area in public open space. This is likely due to public open space being represented as a polygon. While it was difficult to identify a single optimal neighbourhood delineation, results suggested that the neighbourhood built environment was most consistently associated with adult's physical activity when using the 800 m road network buffer.

The remainder of the dissertation turned to focus on how well different delineation methods captured where people spend time. Analyses in these later sections were undertaken using data from the KITC study. Chapter 4 described KITC study methods. Chapter 5 described the GPS inclusion criteria used to create the final GPS dataset which was used as a proxy for exposure.

Chapter 6 explored the degree to which road network buffers represented where children spent time by comparing them with seven-day GPS data. Analyses revealed that residential road network buffers were very poor representations of where children spent time. While this finding was not unexpected, the amount of activity captured by road network buffers was surprisingly low, with less than half of children's seven-day activity captured by road network buffers at a range of scales.

Chapter 7 created a range of activity space delineations and compared these with the GPS data. Results demonstrated that activity space measures were considerably better representations of where children spent time than road network buffers. This was not surprising, since activity space delineations were based on the same GPS data they were compared with. Despite this, the effectiveness of the different activity space delineation methods was varied.

Notably, the measures of activity space commonly used in public health research - the convex hull and standard deviation ellipse – were poor representations of exposure. While they captured a large percentage of activity, they also included large areas that participants never visited. Therefore, these activity space measures are likely to produce homogenous built environment measures that could make it difficult to detect associations between the built environment and health. Furthermore, built environment measures calculated within the convex hull and standard deviation ellipse activity space delineations did not represent the actual environment that participants were exposed to. Researchers should consider using more sophisticated activity space delineation methods; such as the daily path area, temporal local convex hulls, and those based on kernel density estimation, which all provided greater precision in exposure estimation.

Compared with road network buffers, activity space delineation methods better represented exposure to the environment. However, activity space delineation methods require detailed participant location data such as GPS, cellphone, or travel survey data. These data are not always available to researchers as they are expensive and intrusive to collect.

Therefore, Chapter 8 explored improved delineation methods that do not require detailed location data. Five enhancements to the standard road network buffer were proposed. One of these - an enhancement that includes road network buffers around daily destinations other than home - was compared to seven-day GPS data. Results suggested that adding road network buffers around schools may better capture children's exposure than simply increasing the scale of road network buffers around home. Therefore, enhanced road network buffers are a promising delineation method that improves representation of exposure to the environment.

A number of issues raised in this dissertation are worthy of further discussion. Each issue is discussed below.

9.2 Considerations for future research

This dissertation raised a number of issues and considerations for future research. These are discussed below.

9.2.1 The challenge of identifying an optimal delineation method

This dissertation has offered a series of analyses comparing different delineation methods. The first set of analyses, presented in Chapter 3, identified appropriate delineation methods and scales based on the results of statistical models of associations between the built environment and physical activity. This approach was used because it was the most common method of identifying 'optimal' neighbourhood delineations in the literature. While the results of these comparisons are informative, selecting neighbourhood delineations that produce significant results or the strongest effect sizes in the expected direction may not be the most suitable way of selecting optimal or appropriate delineation methods (Spielman, Yoo and Linkletter 2013).

A superior approach may be to select the delineation methods that better capture actual or potential exposure. In other words, instead of choosing methods that produce models with stronger associations between the environment and health, we should consider choosing methods that better capture exposure. Chapters 6, 7, and 8 of this dissertation took this approach by comparing delineation methods with GPS-based exposure data. Further research of a similar nature would improve our understanding of how well different delineation methods and scales represent exposure.

Regardless of the way delineation methods are compared, a theoretical basis for determining how context is delineated is still important. The lack of theoretical and conceptual understanding about which contexts are relevant to health related behaviours and outcomes (Kwan 2012a) can make it difficult to identify a single appropriate context based on theory alone. Therefore, a range of techniques and approaches are likely necessary to allow us to improve delineation of context.

9.2.2 Neighbourhood vs Exposure; Potential vs Actual

Researchers have regularly called for more precise assessment of context by moving beyond residential neighbourhood boundaries towards methods that better capture exposure to the broader environment. In answering this call it is also important to distinguish between actual and potential exposure; a distinction that is rarely mentioned in the literature. As Madsen et al. (2014) note, when measuring and delineating the environment, researchers need to question whether they want to measure actual or potential exposure.

It is important to have clarity regarding this distinction. While current research has predominantly measured potential exposure around the residential neighbourhood, the use of the terms ‘neighbourhood’ and ‘exposure’ is frequently unclear and the residential neighbourhood is often seemingly used as a proxy for actual exposure to the broader environment. However, as this dissertation has shown, the difference between actual (e.g., GPS data) and potential (e.g., road network buffers) exposure can be large. The lack of precision in measurement and the lack of clarity in reporting results are unlikely to further our understanding of relationships between the environment and health.

Despite the lack of precision in measurement, researchers still consistently find associations between the built environment and physical activity. Since we currently lack accurate measures of exposure to the environment, we may be underestimating the relationship between the built environment and health. Improving the precision of our delineation and measurement will enable us to better understand relationships between environment and health.

Future research on delineation of context may benefit from explicit measurement of both potential and actual exposure, especially given: 1) our sparse knowledge about what constitutes appropriate contexts; 2) the potentially large differences between actual and potential exposure and; 3) issues such as selective daily mobility bias (Chaix et al. 2013). Having measures of built environment characteristics of both potential and actual exposure could help us better understand relationships between environment and health.

9.2.3 Measuring 'true exposure'

While it may be desirable to identify delineation methods that best represent exposure (actual or potential) – as opposed to selecting methods that lead to 'optimal' model results, determining what constitutes 'true exposure' is a challenge in itself.

In this dissertation, seven-day GPS data were used as a proxy for actual exposure. The underlying assumption here is that these seven days of mobility data are an adequate representation of a child's life. Yet this is unlikely to be the case. While the minimum data collection duration needed to collect data that represents the true exposure is not known, there is some research to suggest that a minimum of two weeks is necessary to capture variability in travel behaviour (Schlick and Axhausen 2003), with Senbil and Kitamura (2009) noting that a duration longer than two weeks is needed to capture variability in less frequent recreational activities. Furthermore, mobility patterns can be considered across a number of temporal scales (e.g., hourly, daily, weekly, seasonally, yearly, and over the life course; Kestens et al. 2010) and, consequently, the minimum duration of data needed to capture these patterns will also vary.

Missing GPS data is a related issue. Due to large amounts of missing data, the seven-day GPS dataset did not adequately represent the entire seven-day data collection period. The issue of missing data may be partially addressed by improved GPS devices and the use of tracking technologies that do not require satellite visibility (e.g., RFID). However, for now, the issue of missing data is something that researchers will have to contend with.

Without tracking everyone all the time, we may never really know what constitutes true exposure. Like the mythical 'optimal delineation method', 'true exposure' may not be able to be captured. In the absence of measuring the 'true exposure', a practical solution is to ask participants to report usual exposure. Increasingly there are a tools that make this task easier (e.g., http://maptionnaire.com/, VERITAS; Chaix et al. 2012). A combination of participant tracking and self-reported usual activities seems a logical way forward and future research is needed to assess the correspondence between self-reported usual activity and activity measured by tracking technologies.

9.2.4 Whose exposure are we measuring?

GPS technology is a useful tool that allows researchers to measure exposure to the environment more accurately. However, if we use GPS data to help determine the best way to delineate exposure to the environment, then we also need to be sure that the GPS data is representative of the population of interest. The descriptive analyses of GPS inclusion criteria, discussed in Chapter 5, revealed that there were large amounts of missing GPS data, and the participants with the most missing data had specific characteristics. Notably, Māori and Pacific Island participants at schools with lower socio-economic status were excluded disproportionately when applying stricter GPS inclusion criteria.

In New Zealand there is a strong social gradient in health outcomes, with Māori and Pacific Islanders, and those with lower socio-economic status, experiencing poorer health (Hefford, Crampton and Foley 2005, Pearce and Dorling 2006). Consequently, there are equity implications in basing the selection and development of delineation methods – which ultimately influence research results on the relationship between environment and health - on non-representative GPS data. Since there are currently no studies that explore the characteristics of participants excluded when applying GPS inclusion criteria, this is an important area of future research.

9.2.5 Delineation methods need to be considered in combination with methods of representing and measuring the built environment

The primary focus of this dissertation has been on delineation methods. However, it became apparent that how the built environment is measured can determine whether different boundaries capture relationships between the built environment and physical activity, and exposure to the environment. Representation of the built environment within GIS (e.g., point versus polygon) can determine whether a specific feature (e.g., park) is captured by a particular delineation method. This is especially relevant when using road network buffers, which excel at capturing features on or near roads, but are less effective at capturing built environment characteristics located further from the road.

It may be that the common methods of delineating the environment (e.g., buffers) and the common measures of the environment (e.g., counts or densities) do not capture variation within the buffer. Therefore, it is likely that we need to improve both the way we delineate the environment and the way we measure characteristics of the environment.

9.2.6 The importance of time

The temporal dimension is an important aspect of exposure. The longer a person spends in a location, the more plausible it becomes that any effect on behaviour and health, due to the characteristics of that environment, will be magnified. While health researchers are increasingly acknowledging the temporal component, this remains an under-examined issue.

This dissertation has largely focused on the spatial, but has included temporal elements. Namely, the development of temporal localised convex hulls – one of the more promising activity space delineation methods – and the analyses of time spent within various buffers, the results of which added a temporal dimension to analyses.

Expanding the ways we consider and account for time will be important for future environment and health research.

9.3 Conclusion

The conceptualisation and operationalisation of spatial context is an ongoing challenge in built environment and health research, made more complex by the shift in focus from residential neighbourhoods to broader contexts that encompass the multiple locations in which people conduct their daily lives. This shift is associated with the call for more precision in what we measure and brings with it additional challenges in operationalising and delineating these varied spatial contexts.

This dissertation has contributed to this challenge by providing new evidence and insights around delineation methods and how these relate to measures of the environment. It has confirmed what many researchers already know; our current methods of delineating exposure and measuring the environment are most likely inadequate if we want to advance our understanding of the relationship between environment and health. It has also proposed several enhanced methods of delineating exposure. Further research is needed to develop and test methods such as these so that researchers have better tools to measure the environment, and gain a better understanding of the relationship between the environment and health.

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Appendix A. Statement of contribution to datasets and published papers

This thesis used data from two studies of the built environment and physical activity: the URBAN (Understanding the Relationship Between physical Activity and Neighbourhood) study (Badland et al. 2009), and the Kids in the City study (Oliver et al. 2011). The studies are discussed in detail in Chapters 3 and 4 respectively. My contributions to the components of the studies relevant to this thesis are outlined below. All research questions and analyses within this dissertation were made independent of the URBAN and Kids in the City studies.

Contributions to the URBAN study

The URBAN study was a competitively funded project (Health Research Council of New Zealand). I was a named investigator on this study and responsible for GIS components of the study. I contributed to the study design, proposal writing, and responses to referee reports. During the project, I sourced all spatial data, with the exception of the destination data used in the Neighbourhood Destination Accessibility Index. The destination data was compiled by collaborators from the GeoHealth Laboratory, Canterbury University.

The URBAN study is part of a wider international study of the built environment and physical activity (IPEN study). I liaised with the IPEN coordinating centre when calculating the GIS based measures - to ensure that the URBAN study followed IPEN study GIS protocols - and provided feedback on these protocols.

I was responsible for selecting participating neighbourhoods. This involved following the IPEN protocol to calculate a walkability index for all meshblocks in the study cities and selecting neighbourhoods in four quadrants: low walkability and low Māori population; low walkability and high Māori population; high walkability and low Māori population; and high walkability and high Māori population. There were several methodological challenges in this process: creating a neighbourhood from contiguous meshblocks; determining exclusion criteria (e.g., defining urban meshblocks, determining minimum populations); ensuring there was a sufficient population within each neighbourhood; and determining an appropriate process to follow if the required sample was not met within each neighbourhood. I formulated approaches to overcome these challenges and presented recommendations to other members of the URBAN study team. Final decisions were made by the team.

I also devised and mapped the 'random walks'; that is, the random route within each neighbourhood that each research assistant followed. Based on the population of each neighbourhood, the required sample size and expected response rate, I calculated how many houses to sample on each walk.

I geocoded all participant addresses and calculated all GIS measures except for the meshblock level Neighbourhood Destination Accessibility Index (NDAI) measure which was calculated by colleagues at the GeoHealth Laboratory, Canterbury University. For this thesis I re-calculated the NDAI for six additional neighbourhood delineations.

Published papers arising from the URBAN study that I contributed to:

1. (Badland et al. 2009)
Badland, H. M., Schofield, G. M., Witten, K., Schluter, P. J., **Mavoa, S**., Kearns, R. A., Hinckson, E.A., Oliver, M., Kaiwai, H., Jensen, V.G., Ergler, C., McGrath, L., & McPhee, J. (2009). Understanding the Relationship between Activity and Neighbourhoods (URBAN) Study: research design and methodology. *BMC Public Health*, 9(1), 224.

2. (Adams et al. 2014)
Adams, M. A., Frank, L. D., Schipperijn, J., Smith, G., Chapman, J., Christiansen, L. B., Coffee, N., Salvo, D., du Toit, L., Dygrýn, J., Ferreira Hino., A., Lai, P., **Mavoa, S**., Pinzón, J.D., Van de Weghe, N., Cerin, E., Davey, R., Macfarlane, D., Owen, N. & Sallis, J. F. (2014). International variation in neighborhood walkability, transit, and recreation environments using geographic information systems: the IPEN adult study. *International Journal of Health Geographics*, 13, 43.

3. (Witten et al. 2012)
Witten, K., Blakely, T., Bagheri, N., Badland, H., Ivory, V., Pearce, J., **Mavoa, S**., Hinckson, E.A. & Schofield, G. (2012). Neighborhood built environment and transport and leisure physical activity: findings using objective exposure and outcome measures in New Zealand. *Environmental health perspectives*, 120(7), 971.

4. (Badland et al. 2012)
Badland, H. M., Oliver, M., Kearns, R. A., **Mavoa, S**., Witten, K., Duncan, M. J., & Batty, G. D. (2012). Association of neighbourhood residence and preferences with the built environment, work-related travel behaviours, and health implications for employed adults: Findings from the URBAN study. *Social Science & Medicine*, *75*(8), 1469-1476.

5. (Oliver et al. 2014a)
Oliver, M., Badland, H., **Mavoa, S**., Witten, K., Kearns, R., Ellaway, A.,

Hinckson, E.A., Mackay, L.M & Schluter, P. J. (2014). Environmental and socio-demographic associates of children's active transport to school: a cross-sectional investigation from the URBAN study.*International Journal of Behavioral Nutrition and Physical Activity*, 11(1), 70.

6. (Hinckson et al. 2014)
   Hinckson, E. A., McGrath, L., Hopkins, W., Oliver, M., Badland, H., **Mavoa, S**., Witten, K. & Kearns, R. A. (2014). Distance to school is associated with sedentary time in children: findings from the URBAN study. *Frontiers in public health*, 2.

7. (Hinckson et al. under review)
   Hinckson, E.A., Cerin, E., **Mavoa, S**., Oliver, M., Badland, H., Witten, K., Kearns, R.A., Schofield, G. (under review). Specific built environment attributes are associated with sedentary time in population subgroups.

8. (McGrath et al. under review)
   McGrath, L., Hinckson, E.A., Hopkins, W., **Mavoa, S.,** Witten, K., Schofield, G. (under review). Associations between the neighbourhood environment and moderate-vigorous physical activity in New Zealand children: Findings from the URBAN study.

9. (Oliver et al. 2015b)
   Oliver, M., Witten, K., Blakely, T., Parker, K., Badland, H., Schofield, G., Ivory, V.C., Pearce, J., **Mavoa, S.,** Hinckson, E.A., Sweetsur, P., Kearns, R.A. (under review). Neighbourhood built environment associations with body size in adults: Mediating effects of activity and sedentariness in a cross-sectional study of New Zealand adults.

Contributions to the Kids in the City study

The Kids in the City study comprised two distinct but related projects, one funded by the Health Research Council of New Zealand and the second funded by the Royal Society of New Zealand Marden Fund. I was responsible for GIS components and was a named investigator on both the Health Research Council and Marsden studies. Although the qualitative components of the two studies differed the quantitative aspects of each study were combined. This thesis only uses the quantitative Kids in the City data. Throughout this document “Kids in the City study” refers to the combined studies unless explicitly stated otherwise.

I contributed to the study design, proposal writing, and response to referee reports. I sourced most of the GIS data, with the remainder sourced by a fellow GIS analyst. I devised and conducted all Kids in the City related GIS analyses reported in this thesis.

I had a central role in the Kids in the City pilot study, which was conducted prior to the main data collection in order to test data collection protocols. I contributed to the design of data collection protocols, assisted in data collection, analysed the pilot study data, and refined the GPS and neighbourhood walking interview data collection protocols for the main study. I was responsible for designing a GPS in schools exercise for primary school classes. The purpose of this exercise was to introduce potential participants to the study and garner interest and maximise participation.

I was responsible for all data collection using spatial technologies, namely: GIS; GPS; linking GPS and accelerometer data; and linking GPS; digital voice recordings and digital photos. Of these, only the GIS, GPS, and linked GPS/accelerometer data are used in this thesis. I sourced the GPS units and tested them to determine their limits in terms of data storage and battery life. I cleaned, processed and analysed all the GPS data. Since the use of GPS in public health research is relatively new this entailed determining/developing appropriate data cleaning, processing and analysis methods. I developed a novel method to link GPS and travel diary data using sequence alignment algorithms (Mavoa et al. 2011) and contributed to work comparing trips identified with GPS data and those defined by children (Oliver et al. 2014b). GPS methods relevant to this PhD are described in Chapters 4 and 5.

Published papers arising from the KITC study that I contributed to:

1. (Oliver et al. 2011)
   Oliver, M., Witten, K., Kearns, R. A., **Mavoa, S**., Badland, H. M., Carroll, P., Drumheller, C., Tavae, N., Asiasiga, L., Jelley, S., Kaiwai, H., Opit, S., Lin, E., Sweetsur, P., Moewaka Barnes, H., Mason, N., & Ergler, C. (2011). Kids in the city study: research design and methodology. *BMC Public Health*, 11(1), 587.

2. (Mavoa et al. 2011)
   Mavoa, S., Oliver, M., Witten, K., & Badland, H. M. (2011). Linking GPS and travel diary data using sequence alignment in a study of children's independent mobility. *International Journal of Health Geographics*, 10(1), 64.

3. (Oliver et al. 2014b)
   Oliver, M., **Mavoa, S**., Badland, H. M., Carroll, P. A., Asiasiga, L., Tavae, N., Kearns, R., & Witten, K. (2014). What constitutes a ‘trip’? Examining child journey attributes using GPS and self-report. *Children's Geographies*,

12(2), 249-256.

4. (Mavoa et al. 2012)
Mavoa S., Oliver, M., Tava'e, N. & Witten, K. (2012) Using GIS to integrate children's walking interview data and objectively measured physical activity data. *GIS Research UK Conference*, Lancaster, UK.

5. (Badland et al. 2015a)
Badland, H., Donovan, P., **Mavoa, S**., Oliver, M., Chaudhury, M., & Witten, K. (2015). Assessing neighbourhood destination access for children: development of the NDAI-C audit tool. *Environment and Planning B: Planning and Design*, 42, 000-000.

6. (Badland et al. 2015b)
Badland, H., Kearns, R., Carroll, P., Oliver, M., **Mavoa, S**., Donovan, P., Parker, K., Chaudhury, M., Lin, E., & Witten, K. (2015). Development of a system models to visualise the complexity of children's independent mobility. *Children's Geographies*, (ahead-of-print), 1-10.

7. (Oliver et al. in press)
Oliver, M., Parker, K., Witten, K., **Mavoa, S.,** Badland, H., Donovan, P., Chaudhury, M., Kearns, R.A. (accepted). Children's out-of-school independently mobile trips, active travel, and physical activity: An examination from the Kids in the City study *Journal of Physical Activity & Health*.

8. (Oliver et al. under review-a)
Oliver, M., Parker, K. **Mavoa, S.,** Badland, H, Donovan, P., Kearns, R.A., Witten, K. (under review). Associations between the neighbourhood built environment and out of school physical activity and active travel: An examination from the Kids in the City study

Appendix B. Buffer algorithm comparison results

Table 29. Descriptive statistics for the area (km^2) of the different types of buffer at different scales.

	Mean	Median	SD	Minimum	Maximum
400 m					
DN	0.170	0.175	0.065	0.018	0.334
DT	0.183	0.184	0.056	0.026	0.329
GN	0.132	0.132	0.066	0.002	0.319
GT	0.188	0.190	0.056	0.035	0.366
SB	0.135	0.132	0.049	0.032	0.282
500 m					
DN	0.263	0.271	0.099	0.021	0.488
DT	0.272	0.276	0.089	0.026	0.480
GN	0.218	0.221	0.101	0.001	0.445
GT	0.278	0.279	0.090	0.035	0.492
SB	0.204	0.199	0.078	0.032	0.429
800 m					
DN	0.690	0.691	0.244	0.021	1.268
DT	0.668	0.661	0.233	0.026	1.220
GN	0.629	0.626	0.252	0.002	1.183
GT	0.676	0.667	0.236	0.035	1.244
SB	0.510	0.492	0.202	0.032	1.097
1000 m					
DN	1.110	1.111	0.388	0.021	1.990
DT	1.053	1.036	0.369	0.026	1.949
GN	1.036	1.027	0.389	0.002	1.878
GT	1.061	1.042	0.374	0.035	1.946
SB	0.804	0.779	0.318	0.032	1.723
1200 m					
DN	1.642	1.642	0.552	0.021	2.759
DT	1.530	1.514	0.534	0.026	2.799
GN	1.553	1.544	0.555	0.002	2.769
GT	1.538	1.517	0.541	0.035	2.827
SB	1.166	1.122	0.460	0.032	2.471
1500 m					
DN	2.643	2.649	0.836	0.021	4.339
DT	2.425	2.410	0.839	0.026	4.446
GN	2.538	2.511	0.857	0.002	4.299

GT	2.433	2.395	0.852	0.035	4.430
SB	1.840	1.769	0.718	0.032	3.837
1600 m					
DN	3.029	3.053	0.943	0.021	4.991
DT	2.766	2.730	0.955	0.026	5.071
GN	2.926	2.879	0.974	0.002	4.978
GT	2.776	2.707	0.974	0.035	5.119
SB	2.099	1.999	0.820	0.032	4.353
2000 m					
DN	4.843	4.875	1.519	0.021	7.966
DT	4.332	3.987	1.585	0.026	8.076
GN	4.727	4.567	1.571	0.002	8.006
GT	4.350	3.970	1.631	0.035	8.123
SB	3.273	2.966	1.348	0.032	6.817
2500 m					
DN	7.716	7.697	2.497	0.021	12.844
DT	6.731	6.116	2.684	0.026	12.933
GN	7.544	7.537	2.606	0.002	12.800
GT	6.751	6.152	2.746	0.035	13.069
SB	5.028	4.572	2.238	0.032	10.914
3000 m					
DN	11.210	11.267	3.723	0.021	18.788
DT	9.624	9.145	4.078	0.026	18.969
GN	10.967	11.004	3.960	0.002	18.862
GT	9.635	9.175	4.146	0.035	19.069
SB	7.085	6.513	3.341	0.032	15.796

Table 30. Spearman rank correlation coefficients (2 dp, α = 5%, $p < 0.001$) comparing the area of different buffer types at a range of scales.

	DN	DT	GN	GT	SB
400 m					
DN	x	0.91	0.89	0.89	0.84
DT	0.91	x	0.92	0.97	0.93
GN	0.89	0.92	x	0.93	0.91
GT	0.89	0.97	0.93	x	0.95
SB	0.84	0.93	0.91	0.95	x
500 m					
DN	x	0.94	0.94	0.92	0.87
DT	0.94	x	0.96	0.98	0.95
GN	0.94	0.96	x	0.97	0.93
GT	0.92	0.98	0.97	x	0.96
SB	0.87	0.95	0.93	0.96	x
800 m					
DN	x	0.96	0.96	0.95	0.90
DT	0.96	x	0.97	0.99	0.96
GN	0.96	0.97	x	0.97	0.92
GT	0.95	0.99	0.97	x	0.97
SB	0.90	0.96	0.92	0.97	x
1000 m					
DN	x	0.95	0.97	0.94	0.91
DT	0.95	x	0.97	1.00	0.97
GN	0.97	0.97	x	0.97	0.93
GT	0.94	1.00	0.97	x	0.97
SB	0.91	0.97	0.93	0.97	x
1200 m					
DN	x	0.95	0.97	0.94	0.92
DT	0.95	x	0.97	1.00	0.97
GN	0.97	0.97	x	0.98	0.94
GT	0.94	1.00	0.98	x	0.98
SB	0.92	0.97	0.94	0.98	x
1500 m					
DN	x	0.95	0.98	0.94	0.93
DT	0.95	x	0.97	1.00	0.97

GN	0.98	0.97	x	0.97	0.95
GT	0.94	1.00	0.97	x	0.98
SB	0.93	0.97	0.95	0.98	x
1600 m					
DN	x	0.94	0.98	0.94	0.93
DT	0.94	x	0.97	1.00	0.97
GN	0.98	0.97	x	0.97	0.95
GT	0.94	1.00	0.97	x	0.97
SB	0.93	0.97	0.95	0.97	x
2000 m					
DN	x	0.94	0.98	0.93	0.92
DT	0.94	x	0.97	1.00	0.97
GN	0.98	0.97	x	0.97	0.94
GT	0.93	1.00	0.97	x	0.98
SB	0.92	0.97	0.94	0.98	x
2500 m					
DN	x	0.95	0.99	0.94	0.93
DT	0.95	x	0.97	1.00	0.98
GN	0.99	0.97	x	0.97	0.95
GT	0.94	1.00	0.97	x	0.98
SB	0.93	0.98	0.95	0.98	x
3000 m					
DN	x	0.96	0.99	0.95	0.94
DT	0.96	x	0.98	1.00	0.98
GN	0.99	0.98	x	0.98	0.96
GT	0.95	1.00	0.98	x	0.98
SB	0.94	0.98	0.96	0.98	x

Table 31. Spearman rank correlation coefficients (2 dp, α = 5%, $p < 0.001$) comparing intersection counts (Cnt) and intersection densities (Dns) for different buffer types at a range of scales.

	DN		DT		GN		GT		SB	
	Cnt	Dns	Cnt	Dns	Cnt	Dns	Cnt	Dns	Cnt	Dns
400 m										
DN	x	x	1.00	0.91	0.99	0.86	0.98	0.89	0.99	0.88
DT	1.00	0.91	x	x	0.99	0.80	0.98	0.98	0.99	0.97
GN	0.99	0.86	0.99	0.80	x	x	0.98	0.80	0.99	0.80
GT	0.98	0.89	0.98	0.98	0.98	0.80	x	x	0.99	0.96
SB	0.99	0.88	0.99	0.97	0.99	0.80	0.99	0.96	x	x
500 m										
DN	x	x	1.00	0.95	0.99	0.89	0.99	0.93	0.99	0.92
DT	1.00	0.95	x	x	1.00	0.86	0.99	0.98	1.00	0.97
GN	0.99	0.89	1.00	0.86	x	x	0.99	0.86	0.99	0.86
GT	0.99	0.93	0.99	0.98	0.99	0.86	x	x	1.00	0.96
SB	0.99	0.92	1.00	0.97	0.99	0.86	1.00	0.96	x	x
800 m										
DN	x	x	1.00	0.95	1.00	0.94	1.00	0.94	1.00	0.92
DT	1.00	0.95	x	x	1.00	0.95	1.00	0.99	1.00	0.97
GN	1.00	0.94	1.00	0.95	x	x	1.00	0.94	1.00	0.92
GT	1.00	0.94	1.00	0.99	1.00	0.94	x	x	1.00	0.97
SB	1.00	0.92	1.00	0.97	1.00	0.92	1.00	0.97	x	x
1000 m										
DN	x	x	1.00	0.95	1.00	0.95	1.00	0.94	1.00	0.93
DT	1.00	0.95	x	x	1.00	0.96	1.00	0.99	1.00	0.97
GN	1.00	0.95	1.00	0.96	x	x	1.00	0.95	1.00	0.92
GT	1.00	0.94	1.00	0.99	1.00	0.95	x	x	1.00	0.97
SB	1.00	0.93	1.00	0.97	1.00	0.92	1.00	0.97	x	x
1200 m										
DN	x	x	1.00	0.95	1.00	0.96	1.00	0.95	1.00	0.94
DT	1.00	0.95	x	x	1.00	0.97	1.00	1.00	1.00	0.98
GN	1.00	0.96	1.00	0.97	x	x	1.00	0.97	1.00	0.95
GT	1.00	0.95	1.00	1.00	1.00	0.97	x	x	1.00	0.98
SB	1.00	0.94	1.00	0.98	1.00	0.95	1.00	0.98	x	x
1500 m										

DN	x	x	1.00	0.94	1.00	0.98	1.00	0.94	1.00	0.92
DT	1.00	0.94	x	x	1.00	0.97	1.00	1.00	1.00	0.97
GN	1.00	0.98	1.00	0.97	x	x	1.00	0.97	1.00	0.95
GT	1.00	0.94	1.00	1.00	1.00	0.97	x	x	1.00	0.97
SB	1.00	0.92	1.00	0.97	1.00	0.95	1.00	0.97	x	x
1600 m										
DN	x	x	1.00	0.93	1.00	0.98	1.00	0.93	1.00	0.91
DT	1.00	0.93	x	x	1.00	0.96	1.00	1.00	1.00	0.97
GN	1.00	0.98	1.00	0.96	x	x	1.00	0.96	1.00	0.94
GT	1.00	0.93	1.00	1.00	1.00	0.96	x	x	1.00	0.98
SB	1.00	0.91	1.00	0.97	1.00	0.94	1.00	0.98	x	x
2000 m										
DN	x	x	1.00	0.91	1.00	0.98	1.00	0.90	1.00	0.89
DT	1.00	0.91	x	x	1.00	0.95	1.00	1.00	1.00	0.98
GN	1.00	0.98	1.00	0.95	x	x	1.00	0.94	1.00	0.93
GT	1.00	0.90	1.00	1.00	1.00	0.94	x	x	1.00	0.98
SB	1.00	0.89	1.00	0.98	1.00	0.93	1.00	0.98	x	x
2500 m										
DN	x	x	1.00	0.90	1.00	0.98	1.00	0.89	1.00	0.88
DT	1.00	0.90	x	x	1.00	0.94	1.00	1.00	1.00	0.98
GN	1.00	0.98	1.00	0.94	x	x	1.00	0.93	1.00	0.91
GT	1.00	0.89	1.00	1.00	1.00	0.93	x	x	1.00	0.98
SB	1.00	0.88	1.00	0.98	1.00	0.91	1.00	0.98	x	x
3000										
DN	x	x	1.00	0.89	1.00	0.98	1.00	0.87	1.00	0.86
DT	1.00	0.89	x	x	1.00	0.94	1.00	1.00	1.00	0.97
GN	1.00	0.98	1.00	0.94	x	x	1.00	0.93	1.00	0.90
GT	1.00	0.87	1.00	1.00	1.00	0.93	x	x	1.00	0.97
SB	1.00	0.86	1.00	0.97	1.00	0.90	1.00	0.97	x	x

Table 32. Spearman rank correlation coefficients (2 dp, $\alpha = 5\%$, $p < 0.001$) comparing bus stop count for different buffer types at a range of scales.

	DN	DT	GN	GT	SB
400 m					
DN	x	0.98	0.96	0.96	0.96
DT	0.98	x	0.96	0.98	0.97
GN	0.96	0.96	x	0.95	0.96
GT	0.96	0.98	0.95	x	0.96
SB	0.96	0.97	0.96	0.96	x
500 m					
DN	x	0.98	0.97	0.97	0.96
DT	0.98	x	0.97	0.98	0.97
GN	0.97	0.97	x	0.97	0.96
GT	0.97	0.98	0.97	x	0.96
SB	0.96	0.97	0.96	0.96	x
800 m					
DN	x	0.99	0.99	0.99	0.96
DT	0.99	x	0.98	0.99	0.97
GN	0.99	0.98	x	0.98	0.95
GT	0.99	0.99	0.98	x	0.97
SB	0.96	0.97	0.95	0.97	x
1000 m					
DN	x	0.99	0.99	0.99	0.96
DT	0.99	x	0.99	1.00	0.97
GN	0.99	0.99	x	0.99	0.96
GT	0.99	1.00	0.99	x	0.97
SB	0.96	0.97	0.96	0.97	x
1200 m					
DN	x	0.99	1.00	0.99	0.97
DT	0.99	x	0.99	1.00	0.97
GN	1.00	0.99	x	0.99	0.96
GT	0.99	1.00	0.99	x	0.97
SB	0.97	0.97	0.96	0.97	x
1500 m					
DN	x	1.00	1.00	1.00	0.97
DT	1.00	x	0.99	1.00	0.98

GN	1.00	0.99	x	0.99	0.97
GT	1.00	1.00	0.99	x	0.97
SB	0.97	0.98	0.97	0.97	x
1600 m					
DN	x	1.00	1.00	1.00	0.97
DT	1.00	x	1.00	1.00	0.98
GN	1.00	1.00	x	1.00	0.97
GT	1.00	1.00	1.00	x	0.97
SB	0.97	0.98	0.97	0.97	x
2000 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.98
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.98
SB	0.98	0.98	0.98	0.98	x
2500 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.98
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.98
SB	0.98	0.98	0.98	0.98	x
3000 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.98
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.98
SB	0.98	0.98	0.98	0.98	x

Table 33. Spearman rank correlation coefficients (2 dp, α = 5%, $p < 0.001$) comparing dwelling count for different buffer types at a range of scales.

	DN	DT	GN	GT	SB
400 m					
DN	x	0.98	0.97	0.96	0.96
DT	0.98	x	0.97	0.99	0.98
GN	0.97	0.97	x	0.97	0.97
GT	0.96	0.99	0.97	x	0.98
SB	0.96	0.98	0.97	0.98	x
500 m					
DN	x	0.99	0.98	0.98	0.97
DT	0.99	x	0.98	0.99	0.98
GN	0.98	0.98	x	0.99	0.98
GT	0.98	0.99	0.99	x	0.99
SB	0.97	0.98	0.98	0.99	x
800 m					
DN	x	1.00	0.99	0.99	0.98
DT	1.00	x	0.99	1.00	0.99
GN	0.99	0.99	x	0.99	0.98
GT	0.99	1.00	0.99	x	0.99
SB	0.98	0.99	0.98	0.99	x
1000 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	0.99	1.00	0.99
GN	1.00	0.99	x	0.99	0.98
GT	1.00	1.00	0.99	x	0.99
SB	0.98	0.99	0.98	0.99	x
1200 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.99
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.99
SB	0.98	0.99	0.98	0.99	x
1500 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.99

GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.99
SB	0.98	0.99	0.98	0.99	x
1600 m					
DN	x	1.00	1.00	1.00	0.98
DT	1.00	x	1.00	1.00	0.99
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.99
SB	0.98	0.99	0.98	0.99	x
2000 m					
DN	x	1.00	1.00	1.00	0.99
DT	1.00	x	1.00	1.00	0.99
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.99
SB	0.99	0.99	0.98	0.99	x
2500 m					
DN	x	1.00	1.00	1.00	0.99
DT	1.00	x	1.00	1.00	0.99
GN	1.00	1.00	x	1.00	0.98
GT	1.00	1.00	1.00	x	0.99
SB	0.99	0.99	0.98	0.99	x
3000 m					
DN	x	1.00	1.00	1.00	0.99
DT	1.00	x	1.00	1.00	0.99
GN	1.00	1.00	x	1.00	0.99
GT	1.00	1.00	1.00	x	0.99
SB	0.99	0.99	0.99	0.99	x

Table 34. Spearman rank correlation coefficients (2 dp, $\alpha = 5\%$, $p < 0.001$) comparing park area and % park area for different buffer types at a range of scales.

	DN		DT		GN		GT		SB	
	Area	% Area	Area	% Area	Area	% Area	Area	% Area	Area	% Area
400 m										
DN	x	x	0.88	0.87	0.90	0.90	0.88	0.88	0.85	0.86
DT	0.88	0.87	x	x	0.80	0.78	0.98	0.98	0.92	0.92
GN	0.90	0.90	0.80	0.78	x	x	0.81	0.80	0.82	0.81
GT	0.88	0.88	0.98	0.98	0.81	0.80	x	x	0.92	0.92
SB	0.85	0.86	0.92	0.92	0.82	0.81	0.92	0.92	x	x
500 m										
DN	x	x	0.92	0.91	0.90	0.90	0.92	0.92	0.86	0.86
DT	0.92	0.91	x	x	0.84	0.82	0.99	0.99	0.92	0.93
GN	0.90	0.90	0.84	0.82	x	x	0.85	0.84	0.84	0.83
GT	0.92	0.92	0.99	0.99	0.85	0.84	x	x	0.93	0.93
SB	0.86	0.86	0.92	0.93	0.84	0.83	0.93	0.93	x	x
800 m										
DN	x	x	0.95	0.95	0.93	0.94	0.95	0.95	0.88	0.88
DT	0.95	0.95	x	x	0.91	0.91	0.99	0.99	0.92	0.92
GN	0.93	0.94	0.91	0.91	x	x	0.92	0.92	0.85	0.86
GT	0.95	0.95	0.99	0.99	0.92	0.92	x	x	0.92	0.93
SB	0.88	0.88	0.92	0.92	0.85	0.86	0.92	0.93	x	x
1000 m										
DN	x	x	0.96	0.96	0.96	0.96	0.96	0.96	0.87	0.88
DT	0.96	0.96	x	x	0.94	0.94	0.99	0.99	0.91	0.92
GN	0.96	0.96	0.94	0.94	x	x	0.95	0.95	0.88	0.88
GT	0.96	0.96	0.99	0.99	0.95	0.95	x	x	0.92	0.93
SB	0.87	0.88	0.91	0.92	0.88	0.88	0.92	0.93	x	x
1200 m										
DN	x	x	0.96	0.96	0.96	0.96	0.95	0.96	0.84	0.86
DT	0.96	0.96	x	x	0.95	0.95	0.99	0.99	0.90	0.91
GN	0.96	0.96	0.95	0.95	x	x	0.95	0.95	0.86	0.88
GT	0.95	0.96	0.99	0.99	0.95	0.95	x	x	0.91	0.92
SB	0.84	0.86	0.90	0.91	0.86	0.88	0.91	0.92	x	x
1500 m										
DN	x	x	0.94	0.95	0.96	0.96	0.93	0.94	0.78	0.83

DT	0.94	0.95	x	x	0.95	0.95	0.99	0.99	0.88	0.91
GN	0.96	0.96	0.95	0.95	x	x	0.95	0.96	0.82	0.87
GT	0.93	0.94	0.99	0.99	0.95	0.96	x	x	0.90	0.92
SB	0.78	0.83	0.88	0.91	0.82	0.87	0.90	0.92	x	x
1600 m										
DN	x	x	0.94	0.94	0.96	0.97	0.93	0.94	0.78	0.83
DT	0.94	0.94	x	x	0.95	0.95	0.99	0.99	0.88	0.90
GN	0.96	0.97	0.95	0.95	x	x	0.94	0.95	0.81	0.86
GT	0.93	0.94	0.99	0.99	0.94	0.95	x	x	0.89	0.91
SB	0.78	0.83	0.88	0.90	0.81	0.86	0.89	0.91	x	x
2000 m										
DN	x	x	0.92	0.91	0.96	0.97	0.90	0.91	0.74	0.81
DT	0.92	0.91	x	x	0.94	0.94	0.99	0.99	0.88	0.89
GN	0.96	0.97	0.94	0.94	x	x	0.93	0.94	0.77	0.84
GT	0.90	0.91	0.99	0.99	0.93	0.94	x	x	0.89	0.90
SB	0.74	0.81	0.88	0.89	0.77	0.84	0.89	0.90	x	x
2500 m										
DN	x	x	0.89	0.89	0.97	0.97	0.86	0.88	0.69	0.77
DT	0.89	0.89	x	x	0.90	0.90	0.99	0.99	0.88	0.88
GN	0.97	0.97	0.90	0.90	x	x	0.89	0.90	0.72	0.79
GT	0.86	0.88	0.99	0.99	0.89	0.90	x	x	0.90	0.89
SB	0.69	0.77	0.88	0.88	0.72	0.79	0.90	0.89	x	x
3000 m										
DN	x	x	0.84	0.86	0.97	0.98	0.82	0.84	0.70	0.76
DT	0.84	0.86	x	x	0.89	0.89	1.00	1.00	0.91	0.89
GN	0.97	0.98	0.89	0.89	x	x	0.88	0.88	0.74	0.78
GT	0.82	0.84	1.00	1.00	0.88	0.88	x	x	0.91	0.88
SB	0.70	0.76	0.91	0.89	0.74	0.78	0.91	0.88	x	x

Appendix C. Buffer algorithm modelling results

Table 35. Percentage change in physical activity for a 1dph increase in dwelling density across a range of road network buffer types and scales. Bold text indicates a significant association.

Scale	Buffer	% change	confidence interval
400	**DN**	**0.87**	**(0.42 - 1.31)**
400	**DT**	**0.96**	**(0.48 - 1.44)**
400	**GN**	**0.90**	**(0.48 - 1.33)**
400	**GT**	**1.01**	**(0.52 - 1.5)**
400	**SB**	**0.96**	**(0.5 - 1.42)**
500	**DN**	**0.95**	**(0.44 - 1.47)**
500	**DT**	**1.05**	**(0.51 - 1.6)**
500	**GN**	**0.98**	**(0.49 - 1.47)**
500	**GT**	**1.07**	**(0.52 - 1.61)**
500	**SB**	**1.02**	**(0.51 - 1.53)**
800	**DN**	**1.24**	**(0.58 - 1.9)**
800	**DT**	**1.28**	**(0.61 - 1.95)**
800	**GN**	**1.18**	**(0.55 - 1.8)**
800	**GT**	**1.27**	**(0.62 - 1.93)**
800	**SB**	**1.22**	**(0.62 - 1.83)**
1000	**DN**	**1.33**	**(0.59 - 2.07)**
1000	**DT**	**1.43**	**(0.7 - 2.16)**
1000	**GN**	**1.34**	**(0.64 - 2.05)**
1000	**GT**	**1.42**	**(0.7 - 2.14)**
1000	**SB**	**1.35**	**(0.69 - 2.01)**
1200	**DN**	**1.32**	**(0.52 - 2.13)**
1200	**DT**	**1.50**	**(0.71 - 2.28)**
1200	**GN**	**1.48**	**(0.68 - 2.28)**
1200	**GT**	**1.51**	**(0.73 - 2.28)**
1200	**SB**	**1.43**	**(0.72 - 2.14)**
1500	**DN**	**1.59**	**(0.63 - 2.54)**
1500	**DT**	**1.76**	**(0.88 - 2.65)**
1500	**GN**	**1.70**	**(0.76 - 2.64)**
1500	**GT**	**1.80**	**(0.92 - 2.68)**
1500	**SB**	**1.64**	**(0.85 - 2.43)**
1600	**DN**	**1.66**	**(0.68 - 2.64)**
1600	**DT**	**1.81**	**(0.89 - 2.73)**

1600	**GN**	**1.74**	**(0.75 - 2.72)**
1600	**GT**	**1.87**	**(0.96 - 2.78)**
1600	**SB**	**1.69**	**(0.88 - 2.5)**
2000	**DN**	**1.82**	**(0.77 - 2.87)**
2000	**DT**	**2.02**	**(1 - 3.03)**
2000	**GN**	**1.91**	**(0.83 - 2.99)**
2000	**GT**	**2.07**	**(1.06 - 3.09)**
2000	**SB**	**1.91**	**(1.03 - 2.78)**
2500	**DN**	**1.87**	**(0.67 - 3.07)**
2500	**DT**	**2.19**	**(1.07 - 3.31)**
2500	**GN**	**1.97**	**(0.77 - 3.18)**
2500	**GT**	**2.23**	**(1.12 - 3.34)**
2500	**SB**	**2.05**	**(1.11 - 2.99)**
3000	**DN**	**2.00**	**(0.67 - 3.34)**
3000	**DT**	**2.42**	**(1.19 - 3.66)**
3000	**GN**	**2.11**	**(0.76 - 3.46)**
3000	**GT**	**2.45**	**(1.23 - 3.67)**
3000	**SB**	**2.32**	**(1.31 - 3.34)**

Table 36. Percentage change in physical activity for a 1 bus stop increase for a range of road network buffers and scales. Bold text indicates a significant association.

Scale	Buffer	% change	confidence interval
400	DN	0.62	(-0.29 - 1.53)
400	DT	0.62	(-0.29 - 1.53)
400	GN	0.63	(-0.32 - 1.58)
400	GT	0.65	(-0.25 - 1.55)
400	SB	0.55	(-0.36 - 1.46)
500	**DN**	**0.97**	**(0.26 - 1.68)**
500	**DT**	**1.04**	**(0.33 - 1.75)**
500	**GN**	**0.94**	**(0.2 - 1.68)**
500	**GT**	**1.05**	**(0.34 - 1.76)**
500	**SB**	**1.02**	**(0.32 - 1.72)**
800	**DN**	**0.76**	**(0.37 - 1.15)**
800	**DT**	**0.73**	**(0.34 - 1.12)**
800	**GN**	**0.72**	**(0.33 - 1.12)**
800	**GT**	**0.75**	**(0.36 - 1.13)**
800	**SB**	**0.65**	**(0.26 - 1.04)**
1000	**DN**	**0.48**	**(0.21 - 0.76)**
1000	**DT**	**0.50**	**(0.23 - 0.78)**
1000	**GN**	**0.49**	**(0.22 - 0.77)**
1000	**GT**	**0.49**	**(0.21 - 0.76)**
1000	**SB**	**0.46**	**(0.19 - 0.74)**
1200	**DN**	**0.34**	**(0.13 - 0.55)**
1200	**DT**	**0.35**	**(0.13 - 0.56)**
1200	**GN**	**0.33**	**(0.12 - 0.55)**
1200	**GT**	**0.36**	**(0.15 - 0.57)**
1200	**SB**	**0.34**	**(0.13 - 0.55)**
1500	**DN**	**0.25**	**(0.1 - 0.4)**
1500	**DT**	**0.25**	**(0.1 - 0.4)**
1500	**GN**	**0.25**	**(0.1 - 0.39)**
1500	**GT**	**0.25**	**(0.11 - 0.4)**
1500	**SB**	**0.24**	**(0.09 - 0.38)**
1600	**DN**	**0.21**	**(0.08 - 0.34)**
1600	**DT**	**0.21**	**(0.08 - 0.35)**
1600	**GN**	**0.21**	**(0.08 - 0.34)**
1600	**GT**	**0.21**	**(0.08 - 0.35)**
1600	**SB**	**0.22**	**(0.09 - 0.35)**
2000	**DN**	**0.12**	**(0.03 - 0.21)**
2000	**DT**	**0.12**	**(0.03 - 0.21)**
2000	**GN**	**0.11**	**(0.02 - 0.21)**
2000	**GT**	**0.11**	**(0.02 - 0.21)**

2000	**SB**	**0.13**	**(0.04 - 0.22)**
2500	**DN**	**0.06**	**(0 - 0.12)**
2500	**DT**	**0.06**	**(0 - 0.12)**
2500	**GN**	**0.06**	**(0 - 0.12)**
2500	**GT**	**0.06**	**(0 - 0.12)**
2500	**SB**	**0.08**	**(0.02 - 0.14)**
3000	DN	0.04	(-0.01 - 0.08)
3000	DT	0.04	(-0.01 - 0.08)
3000	GN	0.04	(-0.01 - 0.08)
3000	GT	0.04	(-0.01 - 0.08)
3000	SB	0.05	(0.01 - 0.1)

Table 37. Percentage change in physical activity for a 1 intersection per square kilometre increase in street connectivity for a range of road network buffers and scales. Bold text indicates a significant association.

Scale	Buffer	% change	confidence interval
400	DN	0.55	(-0.14 - 1.25)
400	**DT**	**0.28**	**(0 - 0.55)**
400	GN	-0.03	(-0.09 - 0.03)
400	**GT**	**0.19**	**(0.02 - 0.36)**
400	**SB**	**0.18**	**(0.04 - 0.33)**
500	**DN**	**0.64**	**(0.15 - 1.13)**
500	**DT**	**0.48**	**(0.03 - 0.94)**
500	GN	0.12	(-0.02 - 0.25)
500	**GT**	**0.29**	**(0.1 - 0.48)**
500	**SB**	**0.22**	**(0.06 - 0.38)**
800	**DN**	**0.39**	**(0.15 - 0.62)**
800	**DT**	**0.56**	**(0.18 - 0.95)**
800	**GN**	**0.22**	**(0.01 - 0.43)**
800	**GT**	**0.35**	**(0.11 - 0.59)**
800	**SB**	**0.25**	**(0.03 - 0.47)**
1000	**DN**	**0.26**	**(0.1 - 0.41)**
1000	**DT**	**0.63**	**(0.24 - 1.01)**
1000	**GN**	**0.33**	**(0.08 - 0.57)**
1000	**GT**	**0.42**	**(0.15 - 0.69)**
1000	**SB**	**0.34**	**(0.09 - 0.59)**
1200	**DN**	**0.16**	**(0.05 - 0.27)**
1200	**DT**	**0.67**	**(0.25 - 1.1)**
1200	**GN**	**0.31**	**(0.04 - 0.58)**
1200	**GT**	**0.39**	**(0.1 - 0.67)**
1200	**SB**	**0.32**	**(0.05 - 0.59)**
1500	**DN**	**0.11**	**(0.03 - 0.18)**
1500	**DT**	**0.56**	**(0.22 - 0.9)**
1500	**GN**	**0.40**	**(0.1 - 0.7)**
1500	**GT**	**0.50**	**(0.19 - 0.8)**
1500	**SB**	**0.43**	**(0.14 - 0.73)**
1600	**DN**	**0.10**	**(0.03 - 0.17)**

1600	**DT**	**0.86**	**(0.41 - 1.3)**
1600	**GN**	**0.48**	**(0.17 - 0.79)**
1600	**GT**	**0.59**	**(0.28 - 0.91)**
1600	**SB**	**0.53**	**(0.23 - 0.83)**
2000	**DN**	**0.06**	**(0.01 - 0.11)**
2000	**DT**	**1.00**	**(0.53 - 1.48)**
2000	**GN**	**0.63**	**(0.28 - 0.99)**
2000	**GT**	**0.71**	**(0.35 - 1.06)**
2000	**SB**	**0.62**	**(0.28 - 0.95)**
2500	**DN**	**0.03**	**(0 - 0.07)**
2500	**DT**	**0.89**	**(0.39 - 1.39)**
2500	**GN**	**0.70**	**(0.29 - 1.11)**
2500	**GT**	**0.80**	**(0.39 - 1.2)**
2500	**SB**	**0.72**	**(0.34 - 1.09)**
3000	**DN**	**0.02**	**(0 - 0.05)**
3000	**DT**	**0.02**	**(0 - 0.05)**
3000	**GN**	**0.73**	**(0.26 - 1.21)**
3000	**GT**	**0.90**	**(0.44 - 1.36)**
3000	**SB**	**0.82**	**(0.4 - 1.25)**

Table 38. Percentage change in physical activity for a 1 ha increase in park area for a range of road network buffers and scales. Bold text indicates a significant association.

Scale	Buffer	% change	confidence interval
400	DN	-1.12	(-2.68 - 0.43)
400	DT	-0.34	(-1.93 - 1.25)
400	GN	-2.21	(-4.88 - 0.45)
400	GT	-0.47	(-2.11 - 1.17)
400	SB	-1.70	(-4.46 - 1.07)
500	DN	-0.53	(-1.62 - 0.56)
500	DT	-0.55	(-1.79 - 0.69)
500	GN	-1.20	(-2.85 - 0.45)
500	GT	-0.76	(-2.04 - 0.52)
500	SB	-1.52	(-3.68 - 0.64)
800	DN	-0.18	(-0.68 - 0.33)
800	DT	-0.11	(-0.78 - 0.55)
800	GN	-0.34	(-1 - 0.31)
800	GT	-0.15	(-0.84 - 0.54)
800	SB	-0.43	(-1.58 - 0.73)
1000	DN	-0.16	(-0.47 - 0.16)
1000	DT	-0.07	(-0.51 - 0.38)
1000	GN	-0.15	(-0.55 - 0.24)
1000	GT	-0.08	(-0.55 - 0.39)
1000	SB	-0.13	(-0.91 - 0.64)
1200	DN	-0.13	(-0.34 - 0.08)
1200	DT	0.00	(-0.33 - 0.34)
1200	GN	-0.08	(-0.35 - 0.19)
1200	GT	-0.01	(-0.36 - 0.34)
1200	SB	0.03	(-0.56 - 0.61)
1500	DN	-0.06	(-0.2 - 0.08)
1500	DT	0.04	(-0.2 - 0.28)
1500	GN	-0.05	(-0.22 - 0.13)
1500	GT	0.04	(-0.22 - 0.29)
1500	SB	0.15	(-0.28 - 0.58)
1600	DN	-0.04	(-0.17 - 0.09)
1600	DT	0.06	(-0.16 - 0.28)
1600	GN	-0.02	(-0.18 - 0.13)
1600	GT	0.05	(-0.18 - 0.28)
1600	SB	0.20	(-0.19 - 0.6)
2000	DN	0.01	(-0.08 - 0.1)
2000	DT	0.14	(-0.01 - 0.29)
2000	GN	0.02	(-0.07 - 0.12)

2000	**GT**	**0.15**	**(0 - 0.3)**
2000	**SB**	**0.32**	**(0.04 - 0.6)**
2500	DN	0.03	(-0.04 - 0.1)
2500	DT	0.11	(0.01 - 0.21)
2500	GN	0.03	(-0.04 - 0.1)
2500	**GT**	**0.11**	**(0.01 - 0.21)**
2500	**SB**	**0.23**	**(0.03 - 0.43)**
3000	DN	0.04	(-0.01 - 0.09)
3000	**DT**	**0.07**	**(0 - 0.14)**
3000	GN	0.04	(-0.01 - 0.09)
3000	GT	0.07	(-0.01 - 0.14)
3000	**SB**	**0.20**	**(0.06 - 0.35)**

Table 39. Association between percentage park area and physical activity for a range of road network buffers and scales. Bold text indicates a significant association.

Scale	Buffer	coefficient	confidence interval
400	DN	-13.45	(-41.03 - 14.13)
400	DT	-1.75	(-29.81 - 26.31)
400	GN	-19.34	(-53.8 - 15.12)
400	GT	-6.99	(-36.74 - 22.76)
400	SB	-12.42	(-46.86 - 22.01)
500	DN	-13.50	(-42.31 - 15.3)
500	DT	-5.34	(-36.59 - 25.91)
500	GN	-17.83	(-51.99 - 16.32)
500	GT	-10.09	(-42.9 - 22.72)
500	SB	-13.35	(-51.82 - 25.13)
800	DN	-13.31	(-48.1 - 21.48)
800	DT	-13.11	(-55.03 - 28.81)
800	GN	-19.70	(-58.04 - 18.64)
800	GT	-16.10	(-59.45 - 27.26)
800	SB	-29.34	(-81.7 - 23.01)
1000	DN	-20.28	(-56.51 - 15.95)
1000	DT	-13.99	(-60.66 - 32.67)
1000	GN	-18.48	(-59.92 - 22.97)
1000	GT	-18.88	(-67.08 - 29.32)
1000	SB	-28.17	(-88.56 - 32.23)
1200	DN	-21.99	(-59.1 - 15.12)
1200	DT	-11.02	(-63.32 - 41.28)
1200	GN	-17.68	(-62.07 - 26.72)
1200	GT	-17.14	(-71.24 - 36.96)
1200	SB	-22.01	(-90.75 - 46.73)
1500	DN	-16.93	(-55.7 - 21.85)
1500	DT	-7.72	(-65.16 - 49.72)
1500	GN	-13.78	(-60.08 - 32.51)
1500	GT	-11.26	(-71.44 - 48.92)
1500	SB	-11.96	(-89.25 - 65.33)
1600	DN	-12.5	(-52.24 - 27.23)
1600	DT	-0.19	(-58.27 - 57.9)
1600	GN	-8.64	(-54.71 - 37.43)
1600	GT	-4.55	(-65.2 - 56.1)
1600	SB	1.66	(-76.98 - 80.3)
2000	DN	5.27	(-39.91 - 50.45)
2000	DT	41.82	(-19.66 - 103.3)
2000	GN	12.39	(-34.85 - 59.64)
2000	GT	43.83	(-19.42 - 107.08)

2000	SB	55.03	(-30.95 - 141.01)
2500	DN	26.63	(-26.66 - 79.92)
2500	**DT**	**77.77**	**(10.08 - 145.47)**
2500	GN	29.66	(-26.25 - 85.56)
2500	**GT**	**82.00**	**(11.49 - 152.51)**
2500	**SB**	**111.36**	**(7.71 - 215.01)**
3000	DN	56.23	(-3.84 - 116.29)
3000	**DT**	**102.13**	**(29.88 - 174.39)**
3000	GN	52.29	(-10.65 - 115.23)
3000	**GT**	**101.65**	**(26.75 - 176.54)**
3000	**SB**	**185.18**	**(65.36 - 305)**