A GEOSPATIAL APPROACH TO MEASURING THE BUILT ENVIRONMENT FOR ACTIVE TRANSPORT, PHYSICAL ACTIVITY AND HEALTH OUTCOMES

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by

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Abstract

Active transport and physical activity behaviours are recognised as important determinants of a number of health outcomes, including obesity. Over the last decade, there has been a significant amount of research focused on the need to quantify the 'walkability' of neighbourhoods or urban environments as a means of predicting physical activity behaviours. The most common methods used to create indices of walkability focus on a combination of land use mix, street connectivity and dwelling density, as developed by Frank et al., (2005). What is largely missing in this research, however, is a focus on other modes of active transport (such as cycling) and a related recognition of how different delineations (Euclidean and network) of neighbourhoods may affect results.

This thesis investigates the influence of the built environment at a number of spatial levels and different neighbourhood delineations, using both standard and novel methods. This research advances and improves our current understandings of the built environment by being the first to use a novel method based on kernel density estimation, to measure associations between the built environment, active transport, physical activity, and health outcomes in a city in New Zealand (Wellington City). This novel method is used to create an Enhanced Walk Index, improving on standard walk indices by including measures of slope, street lights and footpaths and tracks. In addition, this research is the first to test and validate indices of bikeability and neighbourhood destination accessibility (NDAI), based on the novel method.

Results of the study suggest that the novel Basic and Enhanced Walk Indices had strong significant positive associations with active transport and overweight/obesity. In comparison the standard method had weaker significant associations, potentially indicating previous research has underestimated the effect of the built environment on active behaviours and health outcomes. In addition, the novel indices of bikeability and NDAI also showed significant positive associations with active transport and overweight/obesity, however effect sizes were small. Furthermore, results varied depending on the type of neighbourhood delineation and spatial scale used. However, in general, the network buffer showed stronger associations between indices of the built environment and active transport, physical activity and overweight/obesity.

This research thus strengthens current international and national evidence on how the built environment affects active transport, physical activity behaviours and health outcomes. It expands a preoccupation with walkability to encompass other modes of transport, such as

bikeability. Furthermore it provides an alternative, and potentially more nuanced novel method to assess the relationships between the built environment, active transport, physical activity and health outcomes.

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I would like to thank my supervisors Professor Simon Kingham and Dr. Malcolm Campbell for their guidance, feedback and support. Thank you to Simon for his continuous enthusiasm, encouragement and feedback and for enabling me to present at national and international conferences while completing my PhD. Thank you to Malcolm for his statistical questions and feedback on this research.

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Thank you to my sweetheart Matt for your understanding and unwavering support while finishing this thesis. I would also like to thank Matt's family for their incredible support and kindness throughout this Ph.D. adventure.

Dedication

I dedicate this thesis to my parents, Tim and Theresa and my Grandmother MamMam who have always supported my many pursuits, educational, sports, dance and music.

My grandmother would happily recount her days cycling 5 miles to and from school every day in the hail, rain or snow and was a strong advocate of keeping active. MamMam would often go for short brisk walks every day, either on the road and then around the footpath of her house, until cars seemed to speed up and her sight began to deteriorate. She was an advocate for being physically active no matter what the weather, throughout her life well into her nineties. My father too, is a strong believer in the benefits of physical activity both personally and in the community. Both my parents were actively involved in creating sports facilities and an outdoor gym, accessible to all the community, in our local village. My mother instilled both a love of geography and the importance of being physically active, for both my physical and mental wellbeing. She also makes sure she gets at least a 30 minute walk every day, no matter the weather on the West coast of Ireland. Following conversations with these inspirational family members and a growing awareness of the important impact the built environment in which we live can have on enabling or hindering physical activity, a seed was planted for further investigation. I am forever grateful for the many opportunities I have been given and hope to use my knowledge, skills and experience gained during this PhD to contribute to an improved built environment enabling physical activity behaviours for all.

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Chapter 1. Introduction

Active transport and physical activity behaviours such as walking and cycling are recognised as important determinants of a number of health outcomes. Health outcomes arising out of being physically inactive, overweight and obese are some of the major challenges facing individuals, society and governments in developed countries, but also increasingly in developing countries. Worldwide, trends in physical activity have fallen, we are now more sedentary than ever before, and trends in obesity rates have doubled since 1980 (WHO, 2016). The World Health Organisation (WHO) identified that in 2014 1.9 billion adults in the world were overweight and of those more than 600 million were obese (WHO, 2016).

In New Zealand, there has been a consistent decline in physical activity levels. In 2006/07, one in 10 people were physically inactive, but by 2014/15, one in seven adults were inactive, completing less than 30 minutes of any physical activity in the past week (Ministry of Health, 2015a). In addition, the decline in active transport modes, such as walking and cycling, along with a steady increase in sedentary or inactive transport modes such as using private motor vehicles (PMVs), has further compounded existing health inequalities in relation to overweight and obesity rates in New Zealand. Obesity rates in adults aged over 15 years old have steadily increased from 11 percent in 1989 to 28 percent in 2008, with one in four adults now identified as obese. Similar to other Western countries, New Zealand's population is living longer and facing a growing burden of disease arising from long-term health conditions such as heart disease, diabetes and cancer, which are partially affected by rising obesity levels (Ministry of Health, 2016). These health conditions place enormous pressure on current and future resources within the health system and health care provision in New Zealand (Lal et al., 2012) and worldwide (Withrow and Alter, 2011).

The increased prevalence of overweight and obesity has been attributed to both significant changes in individual lifestyle behaviours such as diet and exercise and the wider food and urban environments. The term 'obesogenic' has been used to describe the obesity-promoting aspects of the food and built environment (Swinburn et al., 1999). In the past, researchers were primarily concerned with understanding individual factors and behaviours such as age, gender, ethnicity, and lifestyle habits including diet and exercise, in explaining the rise in obesity (Macintyre et al., 2002). However, over the last two decades the focus has shifted to the wider context in which people live and share experiences in their daily lives, (Frank et al., 2005; Brownson et al., 2009; Ding and Gebel, 2012; Sallis et al., 2012).

International research focusing on the neighbourhood built environment and its associations with active transport, physical activity behaviours, and health outcomes have increased significantly over the past two decades. This scope of research is multidisciplinary, with scholars from urban planning, transport and public health investigating the links between elements of the built environment, travel behaviour, physical activity and health outcomes. Their goal is to assess individual and population exposures to elements of the built environment in order to identify features that facilitate or hinder active transport and physical activity behaviours. Central to this research is objectively quantifying how 'place', and in particular how different interpretations of the 'neighbourhood' environment can influence active transport, physical activity behaviours and health outcomes.

This thesis builds on existing research focused on the built environment and its associations with active transport, physical activity behaviours and health outcomes. It also addresses current gaps in the field and, in this respect, focuses on three primary challenges, as follows.

First, over the last decade, there has been a significant amount of research that has focused on the need to quantify the 'walkability' of neighbourhoods or urban environments in order to understand and predict physical activity behaviours (Frank et al., 2005; Frank et al., 2010; Leslie et al., 2007; Witten et al., 2012). However, walkability is only one form of active transport. Consequently, other modes of transport used in the daily routines of individuals, such as cycling, remain under-researched (Winters et al., 2010). This research thus expands the focus on active transport by investigating both walking and cycling behaviours and their relationships with elements of the built environment.

Second, the most common methods used to create indices of walkability and 'capture' exposures of the built environment were originally developed over a decade ago (Frank et al., 2005). While these methods have been replicated a number of times, there have been limited attempts to expand and progress quantifying the built environment for walkability and other forms of active transport using alternative potential forms of measurement. This research progresses current understanding in the field of the built environment by being the first to use an alternative method, kernel density estimation (KDE), to measure associations between the built environment active transport, physical activity and health outcomes in a city in New Zealand (Wellington City; see below). This research thus challenges the standard methods of measuring walkability and goes on to explain why a more nuanced way of quantifying walkability is useful and valid. It is also the first study to test and validate additional indices of bikeability and neighbourhood destination accessibility using the novel method, in relation to active transport, physical activity and health outcomes.

Third, in addition to the methods used to ‘capture’ exposures of elements of the built environment, how different delineations of neighbourhoods affect results has not been adequately considered. Understanding which spatial scales are most appropriate to ‘capture’ individual exposures in relation to elements of the built environment is relevant if neighbourhoods are to be designed or transformed to facilitate active transport and physical activity behaviours. This research investigates the influence of the built environment at a number of spatial levels and different neighbourhood delineations, using both standard and novel methods, and thus contributes to the ongoing expansion of methodological discourses on the built environment, active transport, physical activity and health outcomes.

Wellington City in New Zealand was selected as the empirical focus of this research for a number of pertinent reasons. It has an interesting terrain, surrounded by mountains and relatively flat in the city centre and has the highest proportion of active transport commuters and highest employment density in New Zealand (Statistics New Zealand, 2015a). In addition, previous research has found Wellington City to have higher walkability scores that other cities in New Zealand, reflecting a more compact design (Mavoa et al., 2009). This thesis thus also validates previous findings, and contributes new knowledge, to the relationship between the built environment, active transport, physical activity and health outcomes in Wellington City.

1.1 Thesis rationale:

The rationale underpinning this thesis research is first, to validate the standard methods used to quantify the built environment for walking, and second, to advance these methods by addressing some of the central limitations to the standard approach. It is necessary to regularly test and replicate the standard method in different urban environments in order to better determine the reliability, validity and comparability of the method (Brownson et al., 2009). However, it is equally important to develop new and alternative methods to expand and improve our understanding of the relationship between the built environment and health-related outcomes. It is crucial to continually strive to improve methods for measuring the built environment, as they form an important component of the evidence base that in turn supports policy decisions on physical activity interventions and future urban planning.

1.2 Aims and objectives of this research

The over-arching aims of this research are 1) to advance current methods and understanding by developing novel objective measures of the built environment for walking, cycling and neighbourhood destination accessibility; and 2) to comprehensively test associations between the novel indices and active transport, physical activity behaviours, and health outcomes, using available secondary data. Below is a series of measurable objectives listed to achieve the aims of this research.

Objectives:

1. Investigate the evidence of associations between the built environment, active transport behaviours, physical activity, and obesity
2. Give an overview of the literature that objectively measures elements of the built environment for walking and cycling
3. Explore issues of scale and delineation in current literature focused on the built environment and health
4. Develop a set of objective built environment attributes and two versions of the walk index using standard (simple intensity) and novel (kernel density estimation; KDE) approaches. Create these indices using two neighbourhood delineations at a range of spatial scales
5. Develop an Enhanced Walk Index using the novel approach (KDE) for two neighbourhood delineations at a range of spatial scales
6. Develop novel (KDE) bikeability and neighbourhood destination accessibility indices using two neighbourhood delineations at a range of spatial scales
7. Examine and compare the spatial variations between the methods used to create the Basic Walk Indices (BWIs), Enhanced Walk Index (EWI), Bike Index (BI) and Neighbourhood Destination Accessibility Index (NDAI)
8. Test the sensitivity of the novel individual measures and composite indices of the built environment with time spent in active transport, including the influence of home, destination, and route buffers using the New Zealand Household Travel Survey
9. Comprehensively test the validity and associations of each of the standard and novel indices with active transport behaviours using the New Zealand Census
10. Comprehensively test the validity and associations of each of the standard and novel indices with physical activity and health-related outcomes using the New Zealand Health Survey.

Specific research questions related to objectives 7, 8 and 9 are presented in their respective chapters, 5, 6 and 7. Figure 1. provides an overview of the chapters in which each of the objectives are addressed.

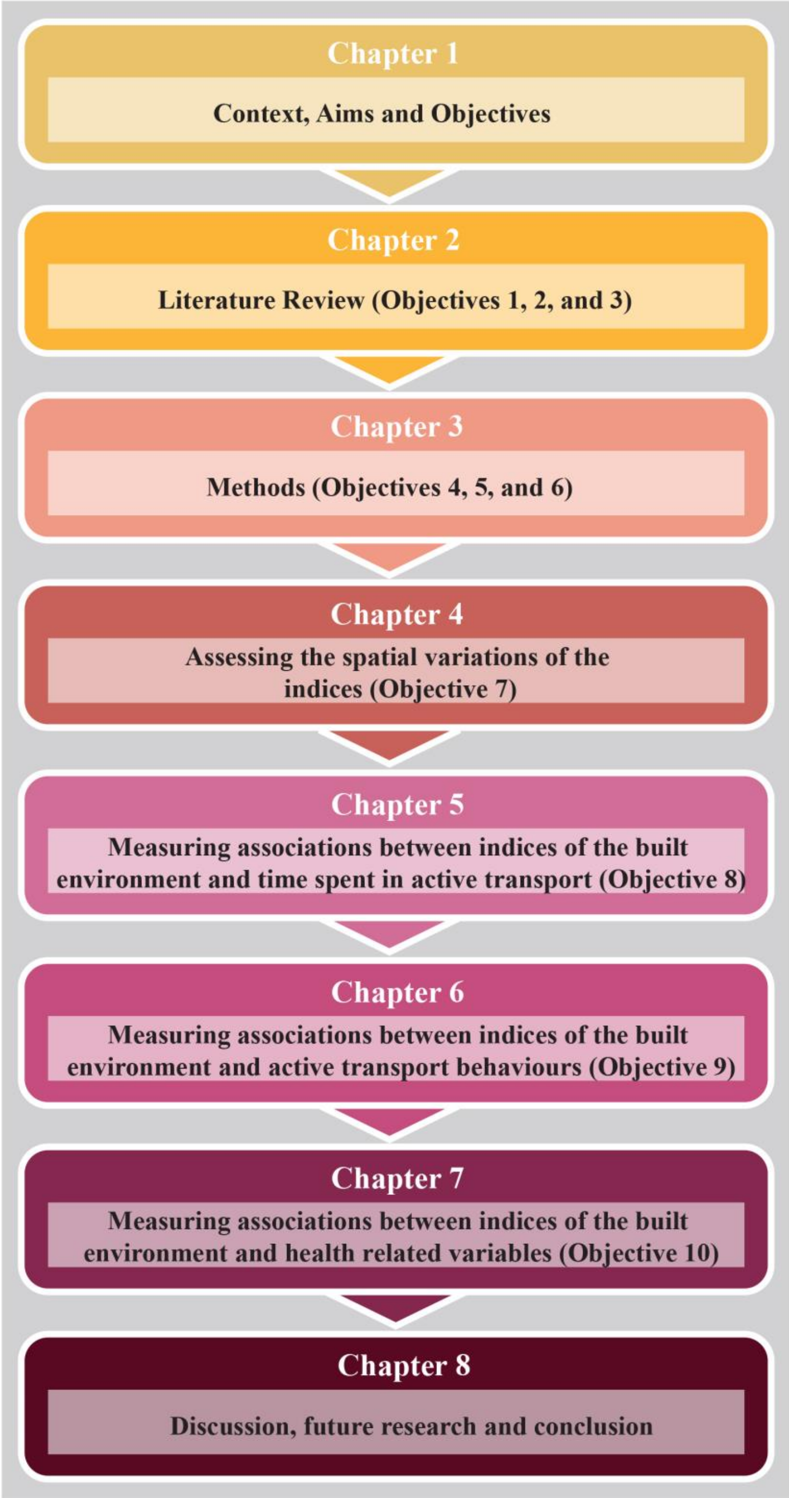


Figure 1. Schema of the objectives addressed in each chapter.

1.3 Thesis structure

Chapter 1 presents the research problem, context, and research need, as well as the research aims and objectives. **Chapter 2** focuses on the review of literature currently relevant to associations between the built environment and active transport behaviours, physical activity, and overweight/obesity health outcomes. In addition, it provides an overview of the standard methods used to measure the built environment and identifies issues relating to neighbourhood delineation and spatial scales. **Chapter 3** addresses the fourth, fifth and sixth objectives of this thesis and develops measures, using standard and novel methods, of the built environment to investigate associations with active transport, physical activity behaviours and health outcomes. **Chapter 4** examines each of the standard and novel composite indices developed in this research. Spatial variations of different neighbourhood delineations and scales are compared and contrasted. **Chapter 5** investigates the associations between individual elements and composite indices of the built environment, around the home, destination and route, (based on the novel method), and time spent walking using the New Zealand Household Travel Survey. This is a standalone exploratory chapter, in contrast to following chapters, which test associations using the composite indices only. **Chapter 6** comprehensively tests the validity of the standard and novel methods used to create indices of the built environment for walking, cycling, and neighbourhood destination accessibility and active transport behaviours using the New Zealand Census. **Chapter 7** comprehensively tests the validity of the standard and novel methods used to create indices of walkability, bikeability and neighbourhood destination accessibility with physical activity behaviours and overweight/obesity. **Chapter 8** presents the discussion of the main findings and an overview of the challenges and opportunities in measuring walkability, bikeability and neighbourhood destination accessibility. In addition, the methodological contributions of this thesis are reviewed in relation to current research developed in the field, along with the limitations and strengths of this research. To conclude, future avenues of research into the built environment active transport and physical activity behaviours are presented.

Chapter 2: Literature Review

2.1 Introduction

The primary objective of this chapter is to examine the evidence and provide an overview of the literature on the relationship between the built environment, active transport, physical activity behaviours and health outcomes. First, a summary of the importance of place in affecting health outcomes is provided along with an introduction to the context versus composition debate (section 2.2). Second, a brief introduction is offered to the main theoretical model (socio-ecological) frequently employed when researching the built environment and health-related behaviours (section 2.3). Third, an outline is provided of the international and national evidence on associations between the built environment, active transport, physical activity and health outcomes (section 2.4). Fourth, a summary of the limitations associated with self-selection are given (section 2.5). Finally, an overview of the literature on the standard and novel methods (developed as part of this research) is given (section 2.6).

2.2 The significance of place

The places in which people live, play, socialise and interact in their daily lives are important for individual health outcomes. For example, people living in rural areas experience better health in comparison to those living in cities as a result of greater opportunities for physical activity (Macintyre and Ellaway, 2003). 'Place' as a concept became relevant from the 1990's (Macintyre et al., 2002). Previous to this, research was driven by the political climate of neo-liberalism, focusing on the role of the individual and their lifestyle choices (e.g. exercise, diet, and smoking) on influencing health outcomes, overlooking the impacts of the built environment (Navarro, 1999, Coburn, 2000, Macintyre et al., 2002). There were a number of limitations, however, in explaining the disparities in health outcomes by focusing solely on the individual. In particular, the increasing prevalence of obesity could not be completely explained by individual, psychological and social factors (Cummins and Macintyre, 2006). A 'new public health' emerged focusing on place and the complex interactions of the social and built environmental influences on individual health and health behaviours (Baum, 1998). The attention was more on the upstream causes of health outcomes and health inequalities rather than the downstream individual lifestyle behaviours of ill-health (Kreiger, 1994). This shift in focus to the importance of place in influencing individual and population health has continued through to current research. Researchers acknowledge and often account for exposure to multiple types of environments (individual, built, social, political), known to influence individual health outcomes (Sallis et al., 2009).

Health Inequalities

Unequal exposure to area-level characteristics, in particular, features of the built environment may be important for influencing health. Researchers are increasingly considering the multiple pathways in which health and health inequalities can be influenced by features of the built environment (Gelormino et al., 2015; Gordon-Larsen et al., 2006; Leyden, 2003; Li et al., 2009; Rosenthal et al., 2007). Gelormino et al., (2015) provide a useful framework to understand the mechanisms through which the built environment could influence health and health inequalities. They propose three potential pathways, 1) the natural environment such as air quality, climate, soil, water and noise pollution, availability of green space; 2) the social context such as social interactions negatively impacted by long commutes, perceptions of safety, availability of public spaces and adequate local infrastructure (schools, libraries, leisure facilities); 3) the behavioural context, reduced physical activity and active mobility due to the need for car use, availability of amenities, perceived quality and proximity of greenspace and recreational facilities (Gelormino et al., 2015). Inequalities in health can be compounded depending on the direction and intensity of effect of each pathway based on the individual or socioeconomic environment (Gelormino et al., 2015).

Context versus Composition

The context versus composition debate centres around whether it is more important to focus on place effects rather than the characteristics of the individual in explaining health outcomes. Compositional explanations attribute geographical disparities in health outcomes to the specific characteristics of individuals living in different areas (Cummins et al., 2005). For example, compositional influences on physical activity and obesity (BMI $\geq$30) can include differences in *ethnicity* (Duncan et al., 2004; Boardman et al., 2005; Sluyter et al., 2011; Derose et al., 2015); *age* (Lobstein et al., 2004; Witlock et al., 2009) *gender* (Borders et al., 2006; Shi and Clegg, 2009; Ladabaum et al., 2014; Seamans et al., 2015); *socioeconomic status* (McLaren et al., 2007; Lovasi et al., 2009; Ogden et al., 2010); *and genetics* (Herring et al., 2014; Albuquerque et al., 2015), (Figure 2).

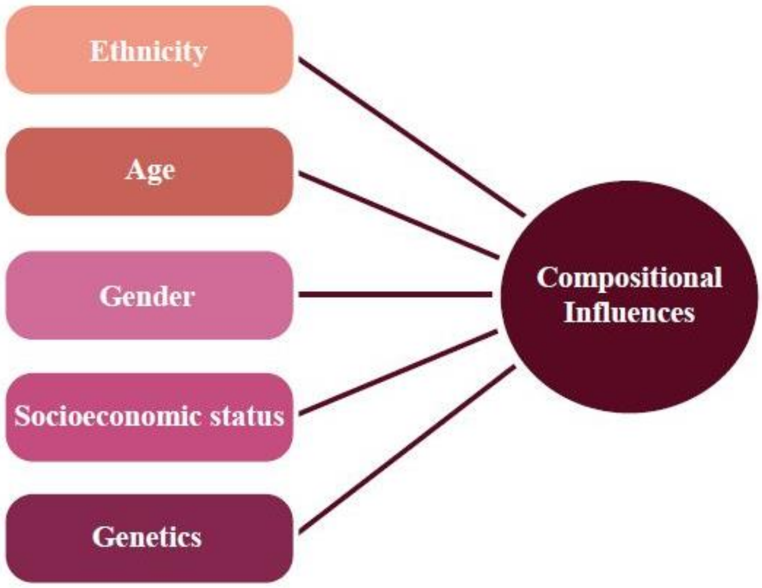


Figure 2. Compositional influences on physical activity and obesity.

Contextual explanations attribute differences in the spatial distribution of health outcomes to characteristics of the environment in which individuals live, independent of the individual residents (Diez Roux and Mair, 2010). A number of examples of contextual influences on physical activity and obesity have been suggested and include *urban sprawl* (Eid et al., 2008; Joshu et al., 2009; James et al., 2013; Congdon, 2016); and *neighbourhood walkability* (Frank et al., 2005; Berke et al., 2007; Sallis et al., 2009; King et al., 2011; Glazier et al., 2014). In the original walkability index (Frank et al., 2005) measures of street connectivity, dwelling density, land use mix were included, later versions of the walkability index additionally included a measure of retail floor area. Further contextual influences include *food environments, (supermarkets, fast food outlets and restaurant*s) (Papas et al., 2007; Ball et al., 2009; Morland and Evenson, 2009; Sallis and Glanz, 2009); *green space* (Coen and Ross, 2006; Ellaway et al., 2005; Mytton et al., 2012; Coombes et al., 2010) and *crime and safety* (Lopez and Hynes, 2006; Kavanagh et al., 2007), (Figure 3).

Figure 3. Contextual influences on physical activity and obesity. Note: the original walkability index included the only three components, later versions of the index also included a measure of retail floor area.

Understanding differences in health outcomes between people and places is continually being investigated and is central to health inequalities research (Mitchell et al., 2000). However, distinguishing between composition and contextual effects on health outcomes is difficult. Macintyre et al., (2002) argued that the individuals' characteristics, as well as households, can be influenced by the local environment. Put simply, the influences of both composition and contextual factors are influenced by one another, which means it is difficult to attribute the causes of health outcomes to one over the other (Figure 4).

Figure 4. Compositional and contextual characteristics interact and influence each other.

This section has provided an overview of the importance of place in health research, and briefly outlined the pathways in which the built environment can affect health and health inequalities. An introduction to the context versus composition debate in understanding health inequalities was also provided. However, further understanding of the multiple pathways by which health can be affected is still needed. In order to achieve this, section 2.3 will outline the socio-ecological model, one of the prevailing models regularly used in public health, urban transport and planning research, to understand determinants of physical activity such as overweight or obesity health outcomes.

2.3 Understanding the relationship between the built environment and physical activity

This section provides a brief synopsis of the prominent models of health within public health, and then an overview of the conceptual framework underpinning this thesis research, namely the socio-ecological model of health. Next, the theoretical frameworks relating to the built environment and active transport and health put forward by Handy et al., (2002) and Pikora et al., (2003) are described.

Approaches to health issues have changed over time. This could be due to changes in the types of diseases prevalent in the community that could not be explained by the traditional biomedical approach. The biomedical approach to health care is centred on the individual's health problems and seeks to fix the problem or condition rather than address the wider determinants of the disease (Davies and Kelly, 1993). While there are advantages to this model, such as developing specialist knowledge to treat common diseases and extend life expectancy through surgical and technological advances, it is, however, limited. It does not address the underlying causes and determinants of the disease, and it is not always an affordable approach, due to the cost of training medical practitioners and developing technologies (Davies and Kelly, 1993). The socio-ecological model, on the other hand, is seen as the responsibility of society as a whole and could be interpreted as a reaction to limitations of the biomedical model, which focuses solely on the individual's health problems. In the socio-ecological model priority is given to prevention rather than the curative or responsive approaches employed by the biomedical model (Davies and Kelly, 1993).

2.3.1 Socio-ecological model of environmental influences on physical activity

Active transport and physical activity behaviours and the processes influencing them are very complex. Identifying and understanding the factors and behaviours that encourage and hinder active transport and physical activity are essential. Therefore, it is useful to have a comprehensive model such as the socio-ecological model to identify the associated factors and determinants of physical activity participation in different environments.

The model was developed and influenced by a number of prominent academics. In 1979, Bronfenbrenner proposed the *Ecological Systems Theory* that focused on the relationship between the environment and the individual. This was followed by McLeroy's *Ecological Model of Health Behaviours* in 1988, which grouped five different levels of influence on health behaviours; however, it failed to include the physical environment. Finally Stokols's *Social Ecology Model of Health Promotion* (1992, 2003) identified the central assumptions underlining the social-ecological model (Glanz et al., 2008).

Socio-ecological models provide a comprehensive approach to examining the multiple level factors that might be determinants of active transport and physical activity. They focus on the interaction between individuals and the social, institutional, community and built environments and policy factors (Sallis et al., 2012). A central principle is that interventions to improve the specific health outcomes are effective at multiple levels – from the individual to the social and built environment, as well as policy levels (Sallis et al., 2006).

Multiple versions of the social-ecological model exist, however a useful and holistic example can be found in Sallis et al., (2006; 2012). They present a socio-ecological model categorising physical activity into four domains of life that describe how people spend their time. The four domains affecting physical activity behaviours include leisure/recreation/exercise, occupation, transportation and household; all of which are influenced by different built environment features and policies, (Sallis et al., 2012). Figure 5 depicts the layers of influences on an individual's health status, and the multiple pathways at the individual, physical activity, social/cultural environment level, built and policy environment levels. Importantly, the model highlights that individual health outcomes should not be investigated in isolation but rather in relation to the various determinants in each of the four domains.

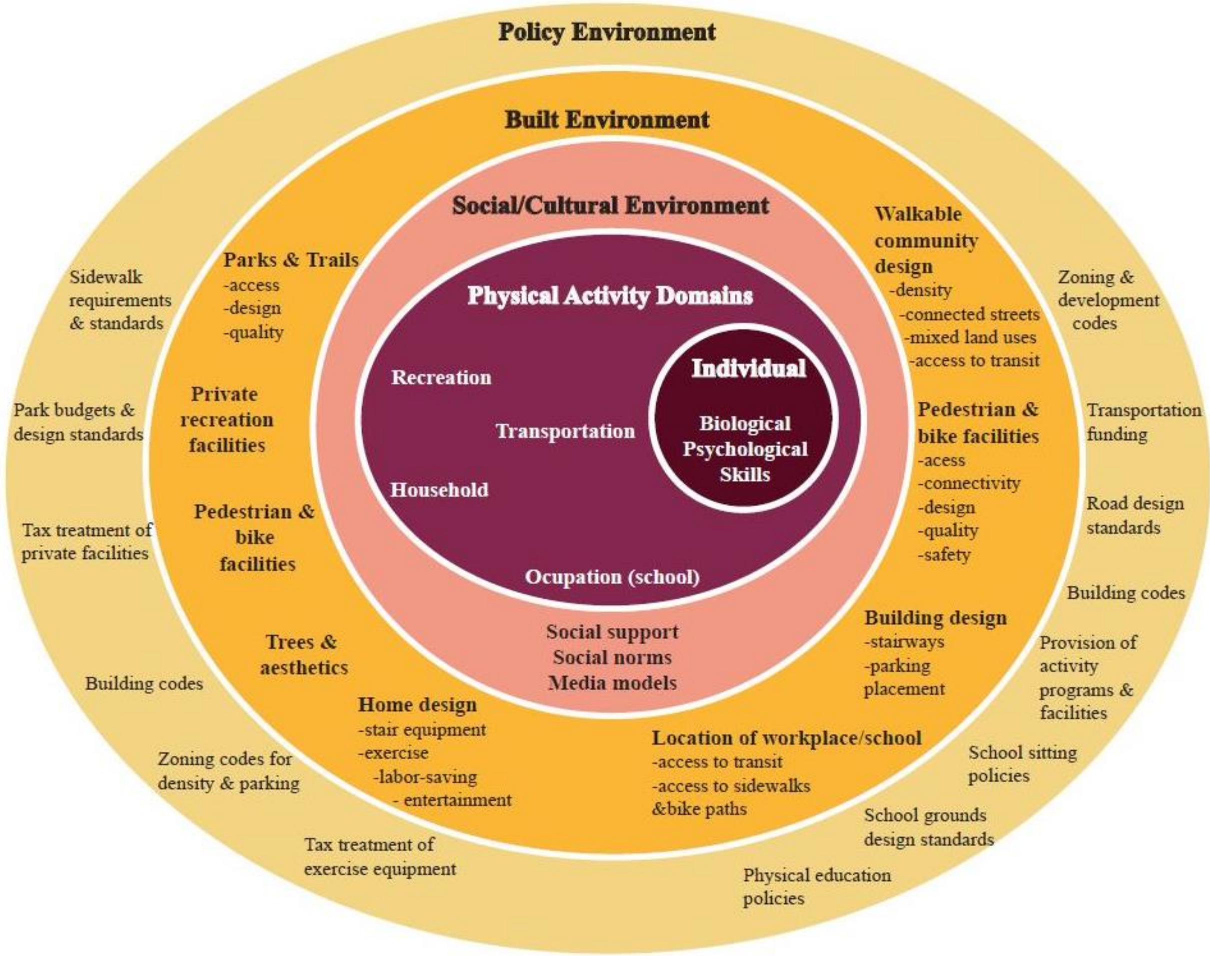


Figure 5. An ecological model of the four domains influencing physical activity behaviours. This is an adapted model by Sallis et al., (2012).

The socio-ecological model offers a way to identify the complex, multilevel and multidimensional impacts of the built environment on an individual's health. It provides a pathway to identifying features that can potentially influence health-related behaviours and outcomes. Understanding the pathways to good health can help create policies that will have the greatest impact on improving physical activity and associated health outcomes for all (Sallis et al., 2012).

2.3.2 Theoretical frameworks of built environment influences on physical activity

Theoretical frameworks specific to the built environment and physical activity are useful when hypothesising relationships between different environmental phenomena and health-related concepts. This section discusses two frameworks, by Handy et al., (2002) and Pikora et al., (2003), that were used to guide this research in analysing relationships between the built environment, active travel behaviours, physical activity and health outcomes.

After reviewing the theoretical frameworks and challenges around the linkages of the built environment and active travel behaviour and physical activity, Handy et al., (2002) concluded that no theoretical framework was available to completely understand these linkages. They went further and suggested combining theories from other disciplines to elucidate the relationships between the built environment and travel behaviour.

Early research from the urban planning and transportation disciplines started to examine how their fields affect human behaviour and health (Handy et al., 2002). Handy et al., (2002:65) defined the built environment as including "urban design, land use and the transportation system" that "encompasses patterns of human activity within the physical environment". They proposed a number of interrelated and often correlated features of the built environment, (Table 1). The transportation system included both the physical infrastructure and services making up the transportation system with the links providing connections. Design of the built environment included aesthetic qualities, land use patterns, the characteristics of outdoor spaces and the interior design of buildings. Finally, land use patterns consisted of the spatial distribution of human activities in the combined built environment and natural landscape (Handy et al., 2002). The importance of scale was also highlighted in each of these definitions.

Table 1. Dimensions of the built environment

Dimension	Definition	Examples of measures
Density and intensity	Amount of activity in a given area	Persons per acre or jobs per square mile Ratio of commercial floor space to land area
Land use mix	Proximity of different land uses	Distance from house to nearest store Share of total land area for different uses Dissimilarity index
Street connectivity	Directness and availability of alternative routes through the network	Intersections per square mile of area Ratio of straight-line distance of network distance Average block length
Street scale	Three-dimensional space along a street as bounded by buildings	Ratio of building heights to street width Average distance from street to buildings
Aesthetic qualities	Attractiveness and appeal of a place	Percent of ground in shade at noon Number of locations with graffiti per square mile
Regional	Distribution of activities and transportation facilities across the region	Rate of decline in density with distance from downtown classification based on concentrations of activity and transportation network

Source: Handy et al., (2002:66)

Pikora et al., (2003) investigated the effects of the physical environment on physical activity. They carried out a survey amongst experts in order to provide a theoretical framework for the assessment of environmental factors, both perceived and objective. The outcome of this survey resulted in models for various types of physical activity, such as walking for recreation, walking for transport, cycling for recreation and cycling for transport in which a number of physical environmental dimensions were determined, (Figure 6).

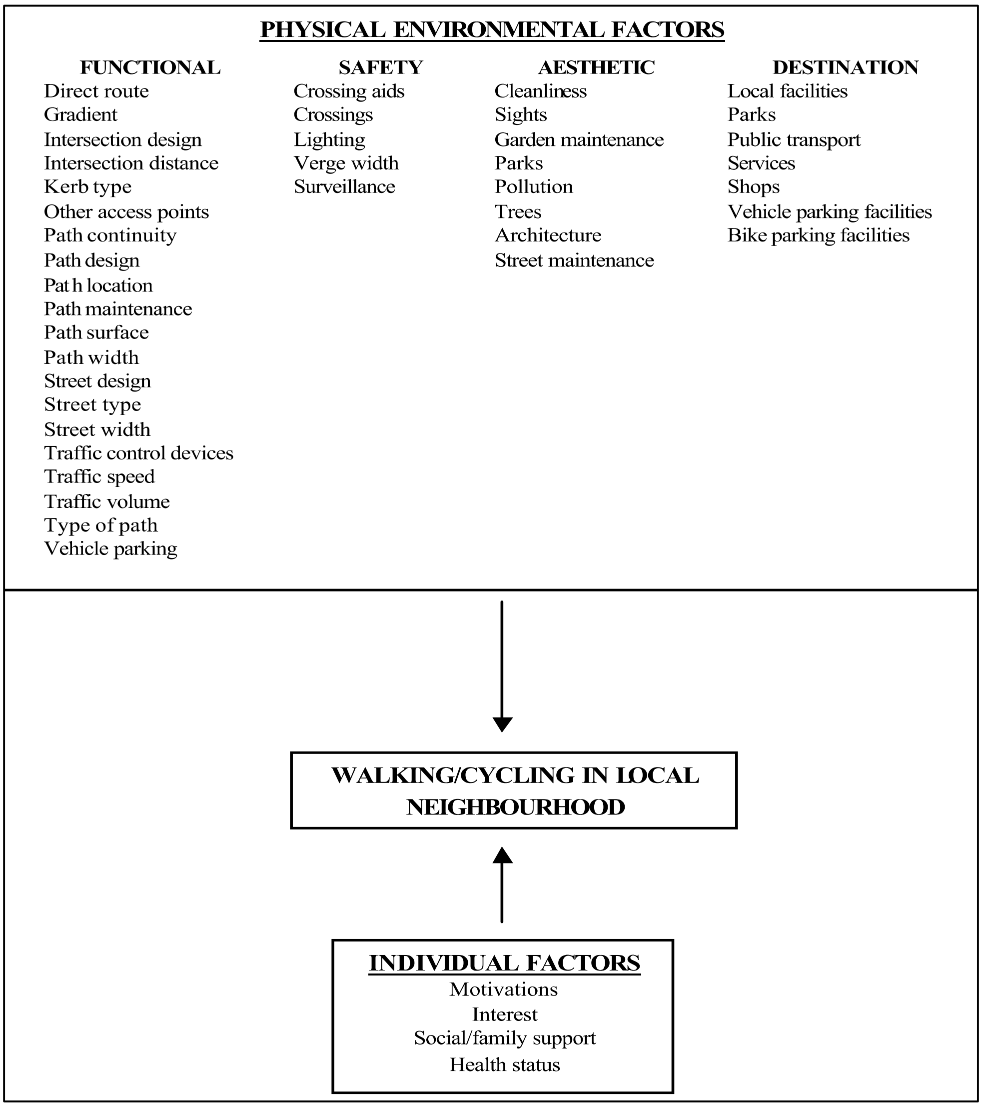


Figure 6. Schema of the physical environmental factors that may influence walking or cycling (Pikora et al., 2003).

The model lists the theoretical individual and physical environmental level factors that can potentially influence walking or cycling in the local environment. This framework by Pikora et al., (2003) continues to be used when examining the subjective and objective influences of the built environment on physical activity levels (Brownson et al., 2009).

To date, there has been limited research focusing on the effects of the built environment on other active transport modes aside from walking. This thesis research draws on some of the physical environmental dimensions presented by Handy et al., (2002) and Pikora et al., (2003) to create objective measures of the built environment and test associations with active transport, physical activity behaviours and health outcomes that go beyond indices of walkability. The particular features used are described in detail in Chapter 3.

2.4 The built environment, active transport, physical activity and obesity

To maintain and achieve good health outcomes it is now widely accepted and recommended that adults should get at least 30 minutes of moderate intensity physical activity at least five days a week, and children up to 60 minutes every day of the week (Ministry of Health, 2012). Individuals are classified as being insufficiently active if they fall below this level of activity. In New Zealand, the 2014/15 national health survey found that only 50.7 percent of adults were sufficiently active to receive adequate health benefits of physical activity (Ministry of Health, 2015a). This is important to consider as physical activity offers a range of health benefits, including counteracting and managing diseases such as obesity and associated co-morbidities of heart disease, type 2 diabetes, some types of cancers (Guh et al., 2009; Ministry of Health, 2015b), high blood pressure (Re, 2009) and depression (Sarwer and Polonsky, 2016).

Increasingly, active forms of transport are recognised as a way to combat rising obesity rates at the population level. Active transport can be defined as a type of non-motorised physical activity such as walking or cycling to get to destinations (Genter et al., 2008). Increasingly, public transport trips are included in as an active form of transport as walking or cycling form part of the whole journey (Villanueva et al., 2008). Active transport has declined in many of the developed countries over the last few decades. This is in part due to increased affluence, population growth and greater access to private motor vehicles, which has resulted in increased growth worldwide in urban mobility since 1960 (Cameron et al., 2004). Distances travelled by car have increased while, at the same time, kilometres travelled using other modes of transport such as walking, cycling and using public transport have decreased.

In New Zealand, Tin Tin et al., (2009) found a 28 percent increase in the number of people driving to work on census days between 1976 and 2006. Other work by Badland et al., (2009) reported a decline in walking and cycling for transport from 14 percent in 1981 to 9 percent in 2006. Importantly, four out of five New Zealanders over 15 years of age indicated that the main mode of transport to work was through driving a motorised vehicle and only one in 14 walked to work, while only one in 40 used cycling as their main mode of transport to work (Badland et al., 2009).

In a more recent report on how people travelled to work on the 2013 census day, Statistics New Zealand reported over seven in 10 people drove a private or company car, truck or van, similar to 2006 figures. The use of public transport across the country increased slightly since 2006 from 3.9 percent to 4.2 in 2013, while other active forms of transport such as walking have remained consistent since 2001, with seven out of 100 walking to work. There was a marginal increase in those who cycled to work from 2.5 percent in 2006 to 2.9 in 2013 (Statistics New Zealand, 2015a). Wellington City was identified as having the highest proportion of active transport users commuting to work on census day compared to the rest of New Zealand. Nonetheless, driving to work remained the main mode of transport in the city, decreasing slightly by 4.6 percent, from 69.2 in 2001 to 64.6 in 2013. Active transport modes such as walking, jogging or cycling were the second most common commute modes, more popular than public transport. In fact, there was a 54.7 percent increase in active transport (walking, jogging or cycling) in the city from 2001 to 2013 (Statistics New Zealand, 2015b). Despite the increase in active travel in Wellington City, the latest results from the New Zealand Household Travel Survey (HTS), 2011-2014, reported 52 percent of total travel time was spent driving and people aged between 35 and 64 spend approximately two thirds of their total travel time driving (Ministry of Transport, 2015). Increasing active transport behaviours and small changes in the daily routines of individuals, such as taking the stairs instead of the lift, parking the car a distance from the destination, and walking an extra few metres, all contribute to the overall daily physical activity levels of an individual. This is important as studies have shown that it is not just the intensity but also the amount of time spent doing some form of physical activity that is important for protective health effects (Warburton et al., 2006).

In a systematic review by (Wanner et al., 2012) they reported a positive association between active transport (walking and cycling) and physical activity, and an inverse relationship between active transport and overweight/obesity. A study in Australia also reported an inverse association between cycling to work and overweight and obesity (Wen and Rissel, 2008). At the same time, car-dominated neighbourhoods were associated with a higher risk of being obese (Frank et al., 2004; Wen et al., 2006; Frank et al., 2007; Cao et al., 2009). For example, physical inactivity research from the United States of America (U.S.A) reported that every extra hour spent commuting by car led to a 6 percent increase in the odds of being obese (Frank et al., 2004). When compared to walking as the main mode of transport, the odds of being obese decreased by 4.8 percent for every kilometre walked. In another study by Wen et al., (2006), examining car use in Australia, individuals driving more than ten times a week were 47 percent more likely to be overweight or obese compared to those driving less than six times a week who had a 30 percent risk. Research in New Zealand by Badland et al., (2008) found that people who walked or cycled to work were more likely to be of a normal body mass size than those who used cars to get to work.

A key finding in the literature on physical activity is that many health outcomes were more pronounced in those who engaged in active transport when compared to those who participated only in leisure-time physical activity (Hu et al., 2003; Bauman et al., 2008). This could be because active transport requires regular travel to and from a destination; the dual purpose of active transport may lead individuals to participate more regularly in physical activity than solely relying on leisure-time activity (Ministry of Transport, 2008). Therefore, incorporation and accumulation of physical activity through active transport in the daily routines of individuals could provide important health benefits.

Key attributes of the built environment regularly examined in relation to active transport, physical activity and overweight/obesity are land use mix (residential, commercial, institutional), household density, location and variety of destinations, street connectivity to reach those destinations easily, and aesthetic qualities such as presence of trees and flowers. Having a variety of destinations such as those regularly accessed in everyday life for work, education, shopping and recreation, has been positively associated with walking and bicycling for transport (Heath et al., 2006; Saelens and Handy, 2008; Durand et al., 2011; Ewing and Cervero, 2010; Fraser and Lock, 2010).

Increased bicycle use is associated with bicycle infrastructure such as paths or trails separating bicycles from traffic (Fraser and Lock, 2010; Krizek et al., 2007). Facilities connecting residential areas and destinations are also important for active transport. Neighbourhoods with street lights and paths, where pedestrians are away from traffic, were found to have residents that walk more and therefore have higher physical activity. Results, however, are not always consistent (Wendel-Vos et al., 2007; Sallis et al., 2009; Ewing and Cervero, 2010; Durand et al., 2011).

Access to public bus and rail stops have also been positively associated with active transport (Sallis et al., 2009, U.S.A); De Bourdeaudhuij et al., 2003, Belgium); Moudon et al., 2007, U.S.A). In fact people who used public transport tended to be more physically active and were less likely to be overweight or obese (Lindstrom, 2008, Sweden). Besser and Dannenberg, (2005) examined the proportion of Americans who achieved the recommended amount of daily exercise walking to and from public transport. They reported 29 percent of the 3312 transit users in the household travel survey walked for greater than or equal to 30 minutes purely by walking to and from transit. In a study in the U.S.A, Saelens et al., (2014) found that transit users had more overall daily physical activity and more total walking than non-transit users.

The association between mixed land use, active transport, physical activity and obesity has been shown to be important. The greater the concentration of different kinds of land use in an area such as residential, commercial, industrial, recreational, and institutional, the lower the obesity prevalence in neighbourhoods (Frank et al., 2004; Mobley et al., 2006). In New Zealand higher levels of walking for active transport was associated with mixed land use as a result of having a greater number and variety of destinations to walk to (Witten et al., 2012). In a study in the United States of America (U.S.A), the proportion of obese individuals declined from 20.2 percent in the lowest land use mix quartile to 15.5 percent in the highest land use mix quartile (Frank et al., 2004). Furthermore, in another U.S.A study, residents living in areas with high mixed land use had a lower BMI than those living in single use environments, due to increased levels of walking and physical activity (Mobley et al., 2006).

In a recent systematic review, by Mackenbach et al., (2014), investigating the associations between the physical environment and weight status in the U.S.A, land use mix and urban sprawl were consistently associated with overweight and obesity. Nonetheless, the review found very little evidence of association for other features of the built environment, such as residential density, walkability, density of food outlets, park area and perceptions of neighbourhood to name a few (Mackenbach et al., 2014). In addition, another recent review concluded that the evidence on associations between attributes of the built environment and adult adiposity remains moderate and they suggest further improvements in measurement methods (Sugiyama et al., 2014). The overview presented here suggests that the evidence is mixed and no clear conclusions can be made on whether urban design features influence active travel behaviours, physical activity and obesity. Further investigation into the relationships between the built environment and active behaviours and overweight/obesity is necessary and as suggested by Sugiyama et al., (2014), improvements in the methods of measurement are required.

Other aspects of the neighbourhood environment such as the social and material context can influence active behaviours and health outcomes. For example, the consequences of neighbourhood deprivation, and scarce access to material resources associated with healthy lifestyles, have been researched in relation to neighbourhood environmental influences on physical activity and obesity. Area deprivation has been linked to proximity to food resources in the U.S.A (French et al., 2000), and green and recreational spaces that enable physical activity in Australia and the United Kingdom (U.K) (Giles-Corti et al., 2003; Stafford et al., 2007). International evidence also indicated that the quality and access of resources available, such as fruit and vegetable shops and recreation facilities, is inversely proportional to neighbourhood deprivation (Lee et al., 2005, U.S.A); Macintyre et al., 1993, U.K). However, New Zealand studies on the influence of deprivation and the quality of resources differed to the international literature in this regard (Field et al., 2004; Pearce et al., 2007a; Pearce et al., 2007b; Pearce et al., 2008). Including measures of neighbourhood deprivation are important in research on the built environment and health in order to account for the social and material contexts in which people live.

This section has outlined the main concepts of the socio-ecological model adopted to understand the relative influences of the physical and social environment and policies on physical activity (Sallis et al., 2006; 2012). The models are driven by the potentiality of positively influencing individual transport behaviours and thus health by changing the physical and social environments (Pikora et al., 2003). Second, a review of the theoretical frameworks proposed by transport, planning and health researchers to investigate the built environment influences on transport and health was provided. Third, an overview of the evidence on the built environment, active transport, physical activity and overweight/obesity was given. The following section briefly reviews the methods and evidence of associations between the indices of walkability and bikeability and health-related behaviours.

2.4.1 Walkability

Walking has been extensively reviewed and measured as a main component of physical activity and active transport. In particular, researchers have measured the built environment for different types of walking such as walking for recreation or exercise (physical activity) or walking to reach a destination (active transport) (Handy et al., 2006). There are a variety of ways the literature describes the latter category, including utilitarian walking, destination-orientated walking, transport-related physical activity, non-motorised travel, and active travel.

A ‘walkable’ environment has been described as one that supports active transport modes including walking, cycling and public transport, enabling equitable access to destinations (Freeman et al., 2013) and enhancing social inclusion (Leyden, 2003), while also improving health outcomes through promoting physical activity engagement (Frank et al., 2010; Witten et al., 2012).

Composite measures of walkability have been developed to measure the degree to which neighbourhood design supports walking. In the U.S.A, Frank et al., (2007) found that a five percent increase in neighbourhood walkability was associated with a 32.1 percent increase in active transport modes and a 0.23 point reduction in BMI in American adults. Saelens et al., (2003), reported that residents within highly walkable neighbourhoods engaged in up to 70 minutes more moderate physical activity per week than those living in low walkable neighbourhoods. Also, those living in low walkable neighbourhoods were nearly twice as likely to be overweight (60 percent) than those living in high walkable neighbourhoods (35 percent). However, other studies in the U.S.A have found there to be no significant association between higher neighbourhood walkability and proportion of residents that are overweight or obese (Berke et al., 2007; Scott et al., 2009).

The standard and most frequently measured attributes of the built environment for walking are street connectivity, household/population density and land use mix, and later studies, when data was available, retail floor area (Brownson et al., 2009). Each of these attributes are regularly associated with walking and physical activity (Frank et al., 2010) and combined to form a walk index (Frank et al., 2005; Mayne et al., 2013). ‘High’ walkability has been defined as areas with high residential densities, high intersection connectivity and good access to a variety of destinations (Frank et al., 2010). In contrast, ‘low’ walkability usually reflects urban sprawl, with areas of low population densities, low street intersections and decentralised development (Lopez-Zetina et al., 2006).

Many of the prominent studies in recent years have measured the degree of influence for each attribute separately (Frank et al., 2004, (U.S.A); Witten et al., 2012, New Zealand) and others have combined them to make a composite index of walkability in Geographical Information Systems (GIS) (Frank et al., 2005, U.S.A; Frank et al., 2010, U.S.A; Mavoa et al., 2009, New Zealand). Briefly, GIS is a tool used to capture, store, analyse, manage and present spatially referenced data (described later in section 2.6) and is regularly used to quantify features of the built environment assumed to influence active transport, physical activity and health outcomes. Combining individual elements into an index is hypothesised to partially address issues of spatial collinearity (the correlation of built environment elements with each other over space) and capture the combined influence of multiple characteristics in one composite index (Brownson et al., 2009; Mayne et al., 2013). In addition, utilising composite indices of walkability resulted in a stronger relationship between the built environment and rates of walking (Frank et al., 2010). The index can be easily communicated and interpreted by urban planning and health policy makers.

However, there are limitations to the standard walk index. As discussed by Handy et al., (2002) and Pikora et al., (2003), multiple aspects of the built environment could influence active transport and physical activity behaviours. Restricting the index to just three components, land use mix, dwelling density and street connectivity (Frank et al., 2005), could potentially limit the applicability and usefulness of the measure. In a later version of the walk index, Frank et al., (2006) included a measure of retail floor area. Many studies have since replicated the four component index to characterise the built environment for walking (Leslie et al., 2007; Owen et al., 2007; Mavoa et al., 2009; Sallis et al., 2009; Mayne et al., 2013; Oliver et al., 2016). One study in Australia compared the three and four component indices, as some countries do not have available data on retail floor area, and found the abridged index was comparable to the four component index and had predictive validity for utilitarian walking in urban areas (Mayne et al., 2013). Even though Leslie et al., (2007), noted that utilising four characteristics was ‘a starting point to a more detailed and informed measure of walkability’ (p.118), the standard walk index has remained largely unchanged in the last decade. By continuously using the same index to quantify walkability it is likely that we are omitting other important features of the built environment related to walking and physical activity. Replicating this method and not including other features, limits it’s reliability and applicability. In addition to the limited number of features included in the standard walk index, the method used to create the index is problematic and not necessarily a true reflection of neighbourhood walkability. The limitations to this method are discussed later in Section 2.6.2.

2.4.2 Bikeability

Bikeability research, compared with walkability research, is a relatively new concept in the literature (Wahlgren and Schantz, 2011; Winters et al., 2010). However, it is already a term used in the United Kingdom and is associated with professional training on the use of a bicycle rather than a measure of cycling accessibility/easiness in the built environment (Christie et al., 2011). Up until relatively recently, cycling has been measured as an auxiliary to walkability, physical activity and active transport research (Wahlgren and Schantz, 2011).

Cycling as mode of transport is cheaper and more sustainable than driving a car (Ministry of Transport, 2008). It is important to consider cycling as a worthy alternative to walking or driving for short to medium sized trips as it is faster than walking, can link with public transport, and allows one to navigate and park in many places for free when compared to those driving cars. The evidence to date, from ecological studies, opinion surveys, and focus groups, suggests that certain attributes of the built environment can influence cycling either positively or negatively (Winters et al., 2010; 2011, Canada). Factors that may influence walking can differ for cycling (Wahlgren and Schantz, 2011, Sweden; Winters, et al., 2011). However, this is not always the case. In an Australian study by Owen et al., (2007) comparing high and low walkability between two areas, they measured the effect on cycling for transport at the same time, and found significantly higher odds for cycling for transport in areas that were defined as highly walkable. Other researchers compared their bikeability index with a walkability index for Metro Vancouver and found a moderate positive correlation (r=0.58) (Winters et al., 2011), indicating areas considered walkable may also be conducive to cycling.

Measuring factors that affect cycling has largely been included in active transport or walkability research rather than as a stand-alone mode. Few studies to date have focused exclusively on cycling and the built environment and, in particular, measuring it objectively through GIS. Early work by Landis et al. (1997) in the U.S.A, produced a 'bicycle level of service' tool, developed from a traditional car based audit of a road-segment. The tool measured the perceived safety and comfort of a hypothetical cyclist with attention to traffic volume and mix, speeds and lane widths. The tool is rooted in concepts from transport engineering and design fields, which limits its application fully to cycling. Cycling as a mode of transport is very different to driving a car and has a set of unique associated travel behaviours.

Recent work by Winters et al., (2010; 2011) in Vancouver, Canada, and Wahlgren and Schantz (2011) in Stockholm, Sweden, has attempted to define and operationalise the concept of bikeability. Their findings indicate this is a growing field of research. The main findings from Winter's et al., (2011) research was that higher intersection density, population or residential density, were associated with a higher likelihood of cycling. The built environment characteristics of the cycling routes were more influential than origin or destination attributes, suggesting that the spatial context and in particular the built environment along the route has a significant influence on active transport behaviours (Winters et al., 2011). Winters et al., (2011) also considered distance of travel and found it to be another fundamental factor when deciding on a transport mode choice. The relevance of trip distance has also been found in other literature on travel influences on behaviours (Cervero et al., 2009; Badland et al., 2008).

Wahlgren and Schantz, (2011) created a self-report questionnaire for individual cyclists to fill in details about their route to work based on eighteen items related to the physical, traffic and social environment and called it the active commuting route environment scale (ACRES). As this was based on subjective (perceived) influences of the environment such as safety, traffic, aesthetics, and commute route infrastructure condition, it could not be measured in GIS. Instead, an average score for a route was created by the tool and was used to compare urban and suburban environments (Wahlgren and Schantz, 2011).

Winters et al., (2011) on the other hand, created a bikeability index through a comprehensive three step research process: firstly, they conducted a population based opinion survey of potential and current cyclists and identified the relative importance of potential motivators and deterrents of cycling, a third of which related to the built environment; secondly, they identified objective measures of the built environment through a two-step travel behaviour analyses, for details see (Winters et al., 2010 and Winters et al., 2011). Finally, they carried out a series of focus group sessions with different types of cyclists (regular, occasional and potential cyclists) to identify and rank the relative importance of the built environment factors previously determined through objective (GIS) measurement. The focus groups also provided more nuanced understandings of how to operationalise conventional concepts (Winters et al., 2013). An example of this is, when asked about highly connected grid based road networks, participants saw this as a positive outcome, encouraging more route choice, but also noted that congested streets with high levels of motorized vehicles were deterrents of cycling (Winters et al., 2013). This insight resulted in modifying the conventional connectivity measure used in walkability indices (intersection density) to include bicycle-friendly roads, that is, local roads and bicycle paths.

Drawing from the empirical evidence obtained through the opinion survey, travel behaviour analysis and focus groups, Winters et al., (2010) synthesised findings and identified a set of readily mapped features that could be objectively measured in GIS. They identified five factors to be included in their composite index: bicycle route density, bicycle route separation, connectivity of bicycle-friendly roads, topography, and density of destinations. They provide a detailed description of the steps taken at each stage of creating the index in GIS, with the intention of easy replication elsewhere. Finally, after testing associations, the index was positively correlated with cycling-to-work.

Increasingly, researchers are calling for walking and cycling to be measured separately because, for example, pedestrians and cyclists navigate the environment differently due to a range of factors including things like topography and street connectivity (Berrigan et al., 2015, U.S.A). Furthermore, this could potentially improve and strengthen future studies. To date there has been limited research investigating the influences of the built environment on modes of active transport other than walkability and their impact on physical activity participation in New Zealand. The evidence suggests that understanding these influences is vital in order to make the necessary changes to the built environment that will ultimately encourage active forms of transport and improve health outcomes.

2.5 Self-selection

Research on the built environment and physical activity is most commonly cross-sectional in nature, which makes it difficult to draw any direct causal relationships. One limitation of this type of research is that an individual's choice of neighbourhood is subject to the concept of self-selection, namely whether physically active individuals choose to live in an area that was active-friendly or by living in such an area they became more physically active (Handy et al., 2006). In addition, many factors such as affordability of housing, employment and school locations, and public transport accessibility can influence an individual's choice of neighbourhood (Badland et al., 2012). Also, other groups in society such as those living in social housing or residential care homes could have limited or no choice but to live in neighbourhoods that are unfavourable to active lifestyle behaviours. However, few studies on the built environment and physical activity have accounted for self-selection because of cross-sectional data limitations. Longitudinal research is the ideal platform to investigate these associations (Brownson et al., 2009). The type of research undertaken in this thesis cannot account for self-selection due to its use of secondary cross-sectional data sources. However, it is acknowledged that any interpretations of results will consider this factor.

2.6 Methods for measuring the built environment for active transport, physical activity and health outcomes

Research on the built environment has proliferated in the last decade. It has generally been measured in three distinct ways, (1) subjectively, through self-reports, or face-to-face interviews, (2) subjectively, through an audit by trained experts and (3) objectively, by measuring in GIS. For a comprehensive and extensive review of how the built environment has been measured for walking, see Brownson et al., (2009). This thesis is concerned with measuring the built environment through objective methods using GIS. The following section will provide a brief introduction to GIS, a tool employed in this research to create objective measures of the built environment. Next, descriptions of the standard methods used to measure elements of the built environment are described. An overview of the alternative method, kernel density estimation (KDE), as utilised in this research, is also provided.

GIS has been defined as the "integration of software, hardware, and data for capturing, storing, analysing and displaying all forms of geographically referenced information" (ESRI, 2008). GIS have been used in a range of settings including urban planning, geography, architecture and statistics research. Increasingly over the last decade, urban planners, public health and health geography researchers have seen GIS as a useful tool to examine the spatial associations between active transport, health outcomes and the built environment (Brownson et al., 2009; Thornton, et al., 2011; Witten et al., 2012).

Measuring the built environment requires tools such as GIS technologies, which are robust, easy to replicate and understand. GIS is increasingly recognised as a more efficient and cost effective solution than other time consuming methods of measuring the built environment such as carrying out face-to-face surveys or auditing (Brownson et al., 2009; Berrigan et al., 2015). In addition, it is useful to communicate and present findings through visual mapping of the results, which can help urban transport and health policy makers identify areas for interventions to improve active transport, physical activity and health outcomes.

2.6.1 Neighbourhood environment and spatial scale

The spatial context of the built environment in which active transport and physical activity takes place is regularly described as the 'neighbourhood' environment. Urban features such as land use mix, street connectivity, dwelling density and composite measures of walkability are linked to individual health-related behaviours, based on geographical location of the individual (Witten et al., 2012; Mayne et al., 2013). Importantly, how the neighbourhood is defined can affect associations between individual behaviours and the built environment (Oliver et al., 2007; Chaix et al., 2009; Vallée et al., 2014). In general, two neighbourhood delineations are regularly used to define the neighbourhood boundary, one based on administrative units and the other based on ego-centric neighbourhoods. A brief summary of each of these neighbourhood delineations is presented next, followed by a discussion of the standard (simple intensity) and novel (kernel density based) methods. These sections provide the theoretical basis for the key methods developed as part of this research, described in detail in Chapter 3.

Administrative units

Secondary data, such as the Census, New Zealand Health Survey, and New Zealand Household Travel Survey, are regularly collected at the administrative unit scale, in particular the meshblock area unit (representing the smallest area unit). The administrative unit does not necessarily reflect where neighbourhoods begin or end. The protocols used to determine the administrative boundaries are often ambiguous, relatively arbitrary, and not well understood in the literature (Brownson et al., 2009; King et al. 2015). This is consistently recognised as a limitation in the literature when using secondary data containing social, cultural and demographic data and then assessing how geography influences the results (Brownson et al., 2009). Neighbourhoods based on this definition might not reflect the behaviours of individuals residing in these areas, known as the 'container effect' (Maroko et al., 2009). For example, individuals may be influenced by built environment features in surrounding meshblocks and access parks or destinations outside of the meshblock in which they reside. Attributing influences of the built environment within the meshblock to individual's behaviours, which take place outside of the meshblock, can lead to incorrect exposure estimates (Duncan et al., 2014; Vallée et al., 2014). In addition, in using administratively created neighbourhoods, there is the potential issue of the modifiable area unit problem (MAUP), whereby if the boundaries were drawn differently there would be significant differences in results (Openshaw and Taylor, 1981). The MAUP is important to consider when analysing spatially aggregated data, as the unit size at which the data is aggregated, in this case the meshblock level, determines the output. If the boundaries of these units are changed or altered, so too will the results of the spatially aggregated phenomenon being measured. The MAUP continues to be an issue in research on the built environment and is widely acknowledged as a limitation (Mitra and Buliung, 2012). There is also an assumption that all parts of the area unit are accessible, for example barriers such as motorways and lakes are assumed to be accessible.

Ego-centric neighbourhoods

Neighbourhoods defined around individual home or work environments are known as ego-centric neighbourhoods and aim to capture the influence of the built environment on active transport, physical activity and health outcomes within this area. Two types of buffers are regularly used to create ego-centric neighbourhoods, Euclidean, based on the straight-line distance from a point and network buffers, based on the street-network distance from a point (Oliver et al., 2007). The Euclidean buffer, similar to the administrative unit, assumes that all areas within the buffer are accessible, which is not necessarily reflective of the features on the ground such as private land, rivers and motorways. On the other hand, the network buffer relies on the accuracy of the underlying road network data which can have varying accuracy and quality (Frizzell et al., 2009). Therefore, previous research has recommended using both types of buffers to determine which is most appropriate to investigate associations with active transport and physical activity behaviours (Oliver et al., 2007).

In contrast to administrative units that are fixed to certain boundaries, ego-centric buffers represent sliding boundaries (Chaix et al., 2009), where the buffers move depending on the address of the individual being assessed. Importantly, the distance or scale is determined by the researcher and commonly hypothesised to represent the distance individuals are likely to walk or cycle within 10 to 20 minutes from their home address (Brownson et al., 2009). Multiple distances ranging from 400m to 3.2 kilometres have been used to test associations with active transport and physical activity behaviours (Brownson et al., 2009). However, determining the most appropriate distance to capture the influence of the built environment is still an area of debate (Oliver et al., 2007; Brownson et al., 2009; Chaix et al., 2009). It is recommended that multiple spatial scales are used when measuring the built environment in order to test the sensitivity of each scale to the behaviour or outcome being measured (Brownson et al., 2009; Leal and Chaix, 2011). In addition, a common theme of research on the built environment and health-related behaviours is measuring the neighbourhood around residential addresses. However, individual active transport and physical activity behaviours can occur in multiple environments outside of the residential address and it is recommended these environments are also included when measuring the built environment (Chaix et al., 2009).

In line with these recommendations, both Euclidean and network buffers were used in this research and created at range of spatial scales, 800m, 1600m and 2400m (described in detail in Chapter 3, section 3.6) and investigated for associations with active transport in Chapter 6, and physical activity and overweight/obesity in Chapter 7. In addition, Chapter 5 examines the sensitivity of each individual measure and composite walk index of the built environment, based on both the Euclidean and network buffers at multiple spatial scales around three different environments, the home, route and destination. An overview of the standard (simple intensity) and novel (kernel density based) methods used to quantify the built environment for active transport and physical activity are presented in the following sections.

2.6.2 Standard method (simple intensity)

The standard methods used most frequently to measure walkability of the built environment in GIS rely on vector data which is made up of three types of data, polygon, line and point (Frank et al., 2005; Leslie et al., 2007; Frank et al., 2009; Mavoa et al., 2009). The method commonly used to create each of the measures included in the walk index has been referred to elsewhere as a simple intensity approach (Buck et al., 2015b). The density of features are calculated as the number of features divided by the size of an area, for example meshblocks or ego-centric buffers, and is referred to as the 'container approach' (Maroko et al., 2009). There are three limitations to the container approach, 1) the simple intensity measure depends on the chosen geographical unit of measurement which does not necessarily reflect the actual environment in which people walk or cycle; 2) the simple intensity measure does account for the proximity, density or clusters of features in relation to one another within the chosen geographical unit; 3) geographical units such as meshblocks vary strongly in size and make it challenging to compare the availability of features such as parks between areas (Buck et al., 2011). In addition, this approach is based on the assumption that the mean values of features of the built environment are distributed evenly within the meshblock or ego-centric buffer (Buck et al., 2015b). However, the location of features within these types of geographical units vary in their spatial distribution (Buck et al., 2015b). This approach implies that people living in these areas have equal exposure to features of the built environment, irrespective of where they reside within the geographical unit (Thornton et al., 2011). Improvements such as individual level density of attributes within a buffer from household locations, proximity based network analysis, activity spaces and accessibility measures using continuous surfaces such as kernel density estimations are ways to overcome this limitation (Thornton et al., 2011). The method described in the following section presents an alternative way to measure the built environment in GIS in relation to active transport and physical activity.

2.6.3 Novel method (kernel density estimation)

Kernel density estimation (KDE) is a weighted density function with point or line data represented by a smoothed continuous map surface divided into a grid of specified cell sizes (King et al, 2015). It estimates the density of kernels over a feature of interest (for example, destinations) within a fixed bandwidth or search radius of the point or line of interest. For example, cells that are located closest to the point or line will receive a weight close to 1 and cells close to the edge of the radius will receive a density value close to 0. The choice of bandwidth is important in this approach, as there is a potential trade-off between bias and variance of the kernel density estimator (Buck et al., 2015b). Fixed bandwidths do not account for the residential density of the areas, which can directly influence the presence or absence of features such as destinations (shops, parks etc.). Adaptive bandwidths based on the underlying residential density may be able to quantify more accurately built environment features adjusted for space and proximity (Carlos et al., 2010; Buck et al., 2015b). For a further discussion on determining the most appropriate bandwidths see Carlos et al., (2010).

KDE is most commonly used in estimating density of crime hotspots (Chainey, 2013; Hart and Zandbergen, 2014), however, some studies have used it to estimate the density of food outlets (Thornton et al., 2012, Scotland; Rundle et al., 2009, U.S.A; Bader et al., 2010, U.S.A), and density of greenspace and recreation facilities (Maroko, 2009). It is not common to use this technique to measure characteristics of the built environment associated with active transport or physical activity behaviours. Only a limited number of studies have used KDE to investigate associations between recreational resources (Diez Roux et al., 2007; in the U.S.A), and neighbourhood destinations (King et al., 2015; in Australia) and physical activity. Only Buck et al., (2011; 2015a; 2015b in Germany), investigated associations between KDE measures of the built environment and physical activity in children. Buck et al., (2011) for example, used KDE to quantify features of the built environment hypothesised to influence physical activity in children. The mean density of features were calculated within administrative areas. They found the KDE approach improved the assessment in comparison to the simple intensity approach (Buck et al., 2011). They combined the features into a moveability index and found modest but significant impact of the built environment on physical activity behaviours in children. In later research, Buck et al., (2015a), calculated the KDE for ego-centered neighbourhoods (vector component) around the child's residence and found it to be a more useful method than the simple intensity method. Their revised and final moveability indices were strongly associated with moderate-vigorous physical activity in children (Buck et al., 2015a).

In Australia, King et al., (2015) is the only study to investigate associations between the density of destinations and two physical activity outcomes in adults, walking frequency and physical activity sufficiency, using three different kernel sizes of 400m, 800m and 1200m. They found for all kernel distances there was significantly greater likelihood of residents walking more frequently if they resided in areas with greater density of destinations. They acknowledged KDE was an underutilised method in GIS applications relating to the built environment and physical activity. KDE presents an alternative method of measuring the built environment at a finer scale than spatially aggregated units such as meshblocks. It improves on the simple intensity method by calculating the proximity and density of features in relation to one another unhindered by geographic unit measurements. In addition, it is a relatively new and underutilised method to measure the built environment in relation to active transport, physical activity behaviours and health outcomes.

2.7 Conclusion

In New Zealand, more than half of the population is insufficiently physically active and two thirds of the population is either overweight or obese (Ministry of Health 2015a). This can have serious implications for individual and population health outcomes and also create future financial burdens on the health system. Importantly, obesity and associated health outcomes are largely preventable diseases. The structure of the food and built environments are central to facilitating or hindering determinants of obesity such as physical activity and active transport behaviours. Identifying and modifying features of the built environment which influence physical activity for multiple purposes is necessary and could have significant health benefits in the long term.

A current area of research is investigating the walkability of neighbourhoods or built environments in order to understand active transport behaviours, and health outcomes such as physical activity and obesity. However, walking is just one form of active transport. There is limited research that has measured, in conjunction with walking, other modes of transport used in the daily routines of individuals, such as cycling, and related them to active transport behaviours and health outcomes. This thesis aims to address this gap by measuring the built environment for walking *and* cycling, while investigating their associations with active transport, physical activity behaviours and health outcomes. Furthermore, methods used to measure walkability and features of the built environment have been limited to simple intensity methods, this thesis intends to contribute to an emerging field of research that is measuring the built environment for physical activity behaviours using an alternative method, KDE (Buck et al., 2015a; 2015b). This study will go further than the standard methods and use KDE to measure the walkability, bikeability and neighbourhood destination accessibility of the built environment in relation to active transport, physical activity and health outcomes.

This chapter provided an overview of the context-composition debate, the socio-ecological model and frameworks to investigate the built environment. Evidence on the relationships between the built environment, active transport, physical activity and obesity were presented. The concepts of walkability and bikeability were also introduced. Finally, a discussion of the methods used to measure the built environment was provided. The following chapter addresses the fourth, fifth and sixth objectives of this thesis and comprises a description of the methods developed and tested in this research.

Chapter 3: Methods for Creating Individual Measures and Indices of the Built Environment

3.1 Introduction

This chapter addresses the fourth, fifth and sixth objectives of this research, which are to develop a set of objective built environment attributes and two versions of the walk index using the standard (simple intensity) and novel (kernel density estimation with a vector component- buffers; KDE) approaches; develop an Enhanced Walk Index using the novel approach; develop novel bikeability and neighbourhood destination accessibility indices. In addition included as part of these objectives is to develop the measures using two neighbourhood delineations at a range of spatial scales. The structure of the chapter is as follows: a brief context to this research is offered (section 3.2); the research design is outlined (section 3.3); along with a description of the study area (section 3.4); the theoretical rationale for selecting the features of each index (section 3.5) and an overview of the methods used to create the individual attributes and composite indices of the built environment is provided (sections 3.6 and 3.7). The chapter concludes with a brief overview of how each index was created (section 3.8).

3.2 Context

Previous research has utilised self-report instruments such as audits to assess attributes of the built environment assumed to influence active transport behaviours, physical activity and health outcomes. However, auditing is subjective and can be a time consuming and costly procedure (Brownson et al., 2009). Recently, GIS has become an important tool in objectively examining the complex relationships between the built environment, active transport, physical activity and health outcomes. An advantage of using GIS, to analyse characteristics of the built environment, is that it enables analysis and remote mapping utilising secondary data sources. Measures commonly included in objective GIS based analysis of the built environment for walking often include land use mix, dwelling density/population density, street connectivity (Frank et al., 2005; Mayne et al., 2013), and retail floor area ratio (Frank et al., 2009; Leslie et al., 2007; Mavoa et al., 2009; Mayne et al., 2013). These measures are occasionally assessed individually and in many cases have been combined into a composite index representing the walkability of the built environment. Advantages of combining the measures into one composite index include addressing issues related to multicollinearity in statistical models (Saelens and Handy, 2008) and ease of interpretation and translation of results (Brownson et al., 2009) for town planners, policy decision makers, transport and health advocates.

Neighbourhoods that are conducive to walking are typically classified as high walkable, and can encourage walking for recreation, utilitarian and transport purposes. There is some debate within the literature as to whether neighbourhoods that are highly walkable are also highly bikeable, that is, whether the factors that encourage walking also encourage cycling to a similar degree (Wahlgren and Schantz, 2011, Winters, et al., 2011). While there is much research on the concept of walkability and measuring specific attributes of the built environment in relation to walking, bikeability is a relatively new concept in the literature. Winters et al., (2010) is one of the first to use GIS to objectively measure attributes of the built environment associated with cycling for active transport. In addition, there is a limited number of research utilising indices of destination accessibility in the neighbourhood environment, which can also be associated with walking and physical activity behaviours (King et al., 2015, Australia; Witten et al., 2011, New Zealand). Indices of walkability, bikeability and neighbourhood destination accessibility can be useful to identify areas that encourage active transport and physical activity behaviours, which in turn can provide evidence for improving the built environment to encourage these behaviours.

3.3 Research design and data

Part of the overall aims of this thesis is to develop indices using available secondary data, in order to see if results on the relationship between the built environment, active transport, physical activity and health outcomes are useful to health policy makers, urban design and transport planners. In this way, methods could be reproduced in a cost-effective manner, utilising existing secondary data to make informed decisions about the built environment and health promoting behaviours.

This research utilises data from three different data sets; the New Zealand Census, (referred to as the Census from this point onwards), the New Zealand Household Travel Survey (HTS), and the New Zealand Health Survey (NZHS) to test and validate associations with elements of the built environment. Brief descriptions of the surveys follow, with more in-depth descriptions in each of their respective chapters, HTS in Chapter 5, Census in Chapter 6 and NZHS in Chapter 7.

The data of each of the three surveys was collected at a number of spatial levels based on administrative boundaries created by councils and central government. In New Zealand, the meshblock level is the smallest geographic unit, with each meshblock representing approximately 110 people (Statistics New Zealand, 2002). It is commonly used as a proxy for the ‘neighbourhood’ in built environment and health research in New Zealand (Mavoa et al., 2009; Witten et al., 2011; Witten et al., 2012; Pearson et al., 2014). In addition, ease of access to secondary data collected at this scale provides a relatively simple path for analysis.

The HTS samples a nationally representative sample of 4,800 individuals continuously from 2003 until 2014 (inclusive). The survey collects information about the day-to-day travel patterns and choices of all types of people and is comprised of a household and an individual personal survey (Ministry of Transport, 2016). Members of households selected are invited to record all their travel over two days and then complete a personal interview reflecting on their travel choices (Ministry of Transport, 2016). The data from both the household and individual surveys is utilised in this research. Individual level data on walkers travel behaviours were generated by combining data from years 2010/11, 2011/12, 2012/13, 2013/14. More detailed information on the HTS and dependent variables used in this research is provided in Chapter 5.

The Census is a nationwide survey completed every 5 years (except in 2011, due to the Christchurch earthquakes) to keep track of population and dwelling numbers and other social areas of interest which helps determine how government funds are spent in the community and plans for future development (Statistics New Zealand, 2016). Area level data from the 2013 Census was obtained for meshblocks where people walked and cycled to work on census day. Chapter 6 provides a more detailed description of the dependent variables utilised from the Census.

The NZHS is a nationally representative survey, which in the past was carried out every 4-6 years up until 2011/12. It is now collected annually since 2011/12 with the current data available until 2015/16. The survey collects information on the health and wellbeing of New Zealanders and provides information to support development of health services, policy and strategy (Ministry of Health, 2016). A more detailed description of the NZHS and the dependent variables used in this research is provided in Chapter 7.

3.4 Study area

The main aims of this thesis are 1) to develop novel objective measures of the built environment for walking, cycling and neighbourhood destination accessibility; and 2) to comprehensively test associations between the novel indices and active transport, physical activity behaviours and health outcomes, using available secondary data. Wellington City is the capital city of New Zealand and the second most populous city in the country (Figure 7), after Auckland. There are a number of reasons why Wellington was selected as the study region. Firstly, the terrain of the central business district is relatively flat while the surrounding terrain, where people live and commute from, is mountainous. The diverse landscape of Wellington City makes it particularly interesting and suitable for testing the novel methods created to assess the walkability, bikeability and neighbourhood destination accessibility of the built environment. Second, Wellington City has the highest employment density (Statistics New Zealand, 2015b) and the highest proportion of active transport commuters in New Zealand (Statistics New Zealand, 2015a) and part of the overall aims of this research is to test the novel walkability, bikeability and neighbourhood destination accessibility indices with active transport behaviours. Third, previous research has found Wellington City to have higher walkability scores, suggest a more dense urban design, than other cities in New Zealand, Christchurch, North Shore and Waitakere[1] (Mavoa et al., 2009). Replicating methodologies and comparing findings with previous research is necessary for determining the reliability and validity of previous findings (Brownson et al., 2009) and adding to the field.

[1] North Shore and Waitakere at the time of research by Mavoa et al., (2009) were cities in the greater Auckland Region, in 2010 they were incorporated into Auckland Council.

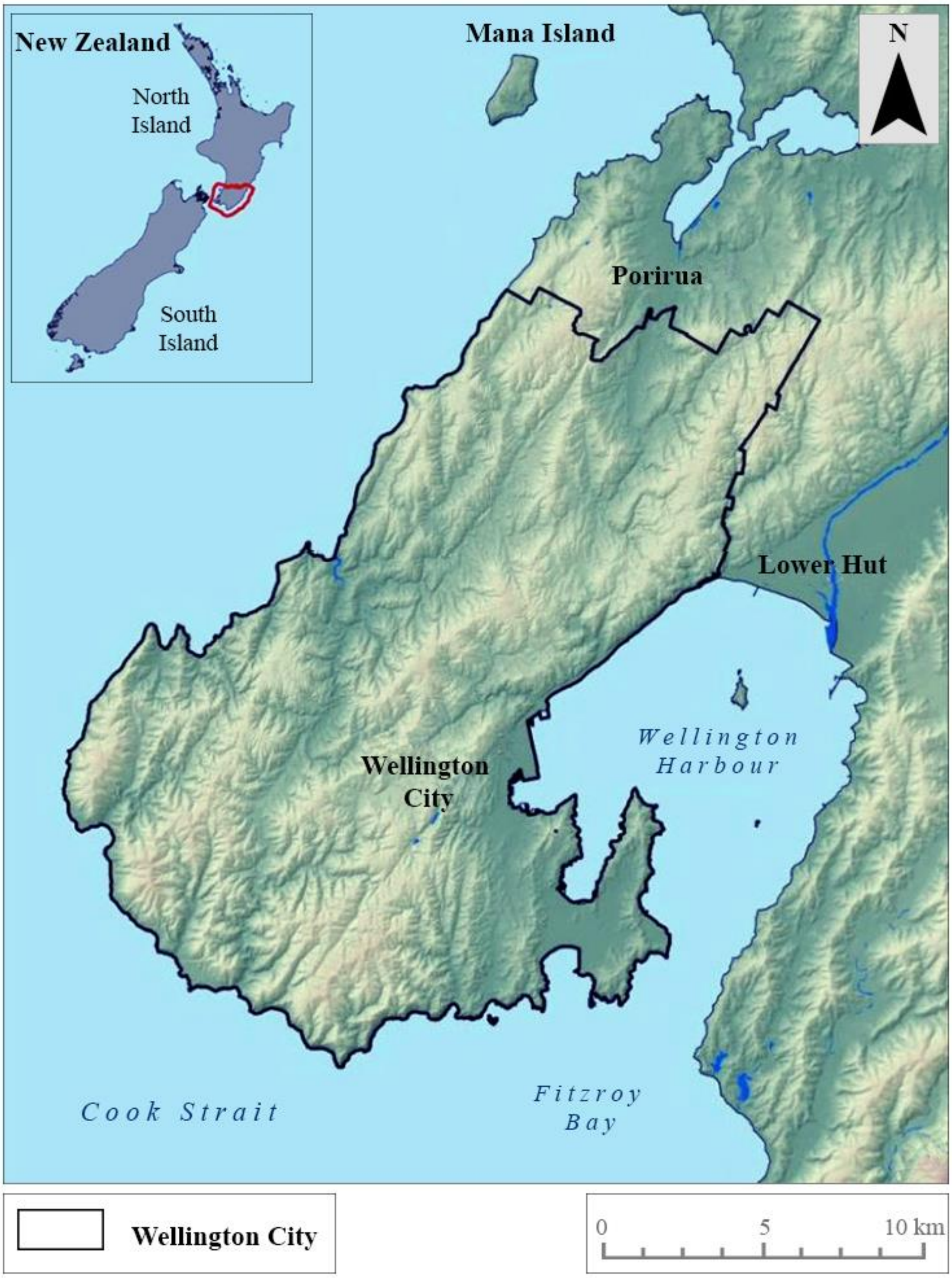


Figure 7. Map of the study region showing Wellington City and the greater Wellington Region.

Population demographics

The usually resident population of Wellington City is close to 191,000 inhabitants, with the overall Wellington Region close to 471,400 inhabitants according to Statistics New Zealand, (2015c). The City accounts for 4.5 percent of New Zealand's population (Statistics, NZ, 2015c). A breakdown of the socio-demographic characteristics of Wellington City in comparison to the total population of New Zealand is provided in Table 2. Briefly, the median personal income for individuals over 15 years old in 2013 was NZ$37,900 per annum, nearly ten thousand more than the national median income, NZ$28,500 per annum. The percentage of post-school qualifications is also higher in Wellington City than the national average. These statistics could be expected as most of the central government departments, with highly qualified civil servants, are located in Wellington City.

Table 2. Socio-demographic characteristics in 2013 of Wellington City and New Zealand

Characteristics	Wellington City	New Zealand
General population	190,959	4,242,048
Māori population	14,433	598,602
Median age 2013 (years)	33.9	35.9
Median personal income in $NZ (>15 years)	37,900	28,500
Post-school qualification (%)	55.1	46.3
Population under 15 years (%)	17.3	20
Population increase 2006-2013 (%)	6.4	5.3

Source: Statistics New Zealand, (2013).

3.5 Theoretical framework for objectively measuring the built environment

This research includes elements from the two frameworks (Handy et al., 2002 and Pikora, 2003) discussed in Chapter 2, section 2.3.2, which formed the basis in which to build indices for walking, cycling and neighbourhood destination accessibility. Initially at the beginning of the research process, a number of features of the built environment, identified in these frameworks, were selected for inclusion in the walk and bike indices. A list of up to twenty features were generated and requests for data were sent to Auckland, Wellington and Dunedin City Councils. Wellington City Council was the only authority, within the available time frame, able to provide data for many of the features included in the list and was therefore selected for this study. Other sources such as Land Information New Zealand, Statistics New

Zealand, Zenbu.co.nz and the Ministry of Health were also used to source data relating to features and destinations of the built environment hypothesised to influence active transport, physical activity and health outcomes (Tables 3 and 4).

Three features of the built environment regularly included in the walk index include land use mix, street connectivity and dwelling density. These features were included in the standard and novel basic walk indices (BWIs) developed as part of this research and described in section 3.7.1 and section 3.7.2. Following preliminary analysis of both methods, an Enhanced Walk Index (EWI) was created in order to advance, test and validate the novel method with secondary data on active transport, physical activity behaviours and health outcomes. The additional features of slope, street lights and footpaths and tracks were included as they link to the features described in the framework described by Pikora et al., (2003) and are hypothesised to influence active transport and physical activity behaviours. Evidence to support the hypothesised associations between each element of the built environment, included in the novel indices (BWI and EWI), and active transport and physical activity are presented as the rationale and then followed by a description of the specific methods used to create the measures (section 3.7.1 and section 3.7.2).

3.6 Methods for operationalising neighbourhood exposure

Creating valid and replicable measures of the built environment are essential to refining our understanding of the relationship between the built environment, active transport modes, physical activity and health outcomes (Brownson et al., 2009; Sallis et al., 2009). Part of the fourth, fifth and sixth objectives of this research is to create two types of buffers at multiple scales of the built environment; and investigate how different neighbourhood delineations and scales impact on associations between individual and composite indices of the built environment, active transport, physical activity and health outcomes. The next section begins by providing a brief overview of the buffers and spatial scales used in this research.

Neighbourhood delineations and scale

While touched upon briefly in the previous chapter, neighbourhood delineations such as administrative units (meshblock) and in particular ego-centric buffers remain the most frequently utilised methods intended to capture 'neighbourhood' exposures of features of the built environment. They have been used as a way to manage issues arising from the 'modifiable area unit problem' (MAUP) which can result in artificial geographic units based on arbitrarily defined boundaries (Brownson et al., 2009). Buffers can be created around individual home addresses, work places, meshblock based population weighted centroids (PWCs) and the meshblock area unit. One limitation commonly reported is that results can vary dramatically depending on the type of buffer used, whether Euclidean (circular) or network (line based) (Oliver et al, 2007; Brownson et al., 2009). Euclidean buffers may capture built environment features such as rivers, lakes, railways and cliffs, which may be inaccessible to walkers and cyclists (Oliver et al., 2007). It is for this reason that studies are increasingly using road network buffers (henceforth referred to as network buffers) to define accessible areas individuals can walk or cycle to by road (Oliver et al., 2007; Witten et al., 2011; Witten et al., 2012). There have been a limited number of studies comparing both types of buffers across a range of spatial scales (Oliver et al., 2007). The novel methods developed as part of this research aims to contribute to the debate and evidence base, by investigating built environment measures using Euclidean and network buffers at a range of spatial scales.

There are no universally accepted spatial scales to investigate associations between active transport and physical activity with scales ranging from 400m to 3.2 km across many studies (Brownson et al., 2009). More recently, distances of 200m-1600m around an individual's home have been used to represent different neighbourhoods and are seen as 'walkable' distances to destinations (Villanueva et al., 2014). For example, Forsyth et al., (2008) used buffers of 200m, 400m, 800m and 1600m to represent different walkable environments, (without defining a time in relation to these distances); Moudon et al., (2005) used a buffer size of 3km, to represent a comfortable cycling range of 20 minutes; Heinin et al., (2010) in their overview of the cycling and commuting literature concluded that shorter distances, access to good storage and a greater mix of destinations are factors that increase cycling share. The spatial scales used in this research, 800m, 1600m, 2400m, were selected to represent typical distances people can walk or cycle for transport, utilitarian or leisure purposes within 10, 20 or 30 minutes. Initially however, distances of up to 6.4km were considered for capturing the bikeability of neighbourhoods in this research, however due to the intense processing required in ArcGIS and multiple difficulties running the models, shorter distances were used instead. Also, previous research have used distances of up to 3km in their analysis (Moudon et al., 2005).

The Euclidean and network buffers were created around meshblock based PWCs, to represent different types of neighbourhoods at a range of spatial levels (800m, 1600m, 2400m, Figure 8). In an ideal research study, the geographic locations of individual participants could be used to test the associations with physical activity, such as research by King et al., (2015).

However, secondary data such as the data analysed in this thesis, Census and NZHS, is usually only provided at the meshblock area unit to ensure confidentiality of survey participants. Therefore, meshblock based PWCs were used as a proxy measure for individual participants in the analyses presented in Chapters 6 and 7. However, individual address points were available for the HTS, therefore Euclidean and network buffers were created at multiple scales based on individual home and destination addresses (described in detail in Chapter 5). Figure 8 presents an example of the Euclidean and network buffers utilised in this research. These different neighbourhood delineations represent potential areas of exposure to diverse built environment characteristics.

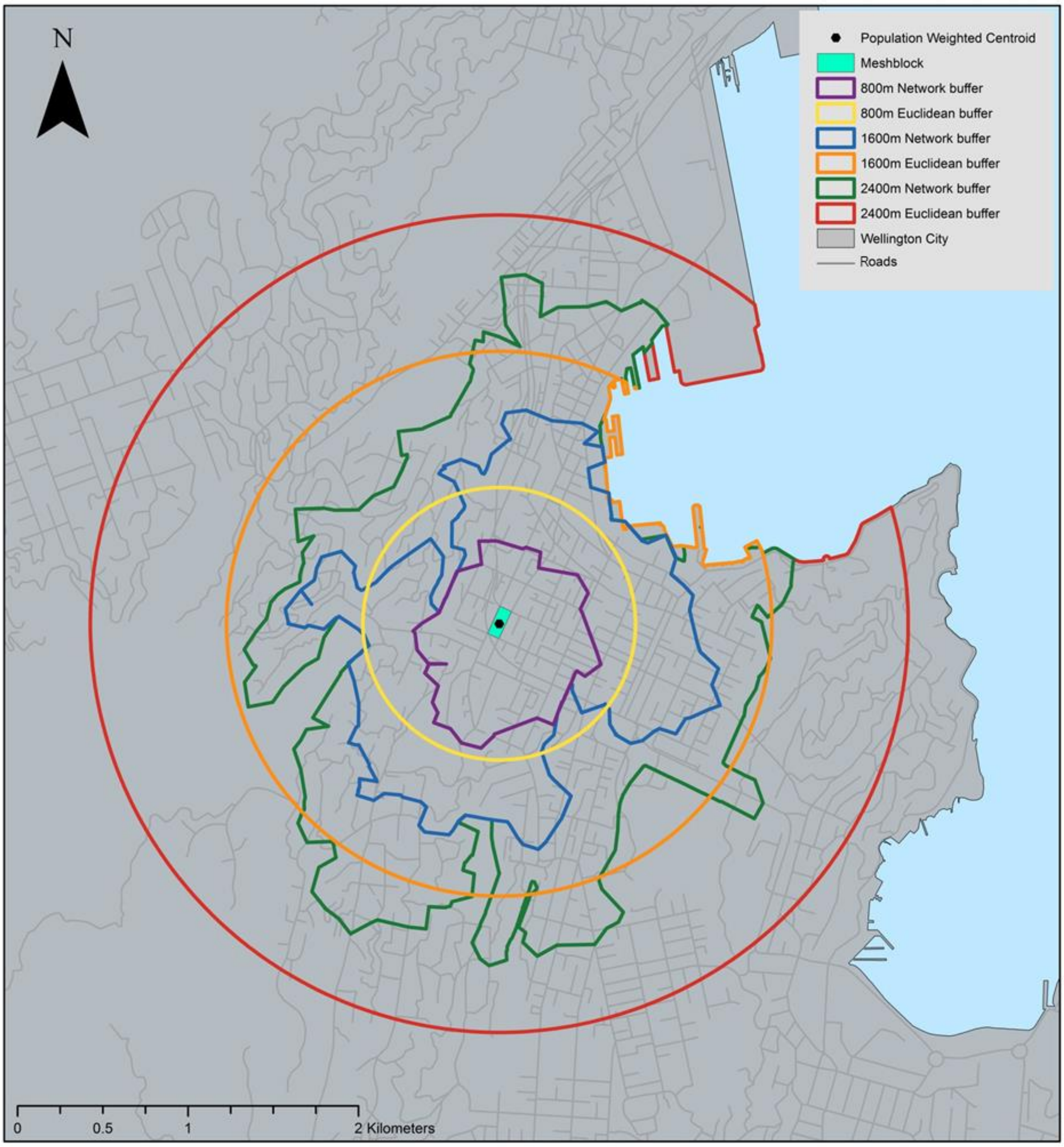


Figure 8. Example of Euclidean and network buffers around a meshblock based population weighted centroid in Wellington City. The extent of each buffer was clipped to the coastline of Wellington City.

In relation to the meshblock based PWCs utilised in this research, it should be noted that, even though there are 2,023 meshblocks in Wellington City, only meshblocks with address points of dwellings were included in the analysis (n=1,988). 35 meshblock based PWCs were removed after identifying that these meshblocks were made up of train stations, parks and hills without any population residing there (Figure 9). This research is interested in measuring the built environment around hypothetical home addresses of participants; therefore, meshblocks without any dwellings were removed. Moreover, destinations such as parks and train stations are already accounted for in the neighbourhood destination accessibility index, described further on in section 3.6.2.9.

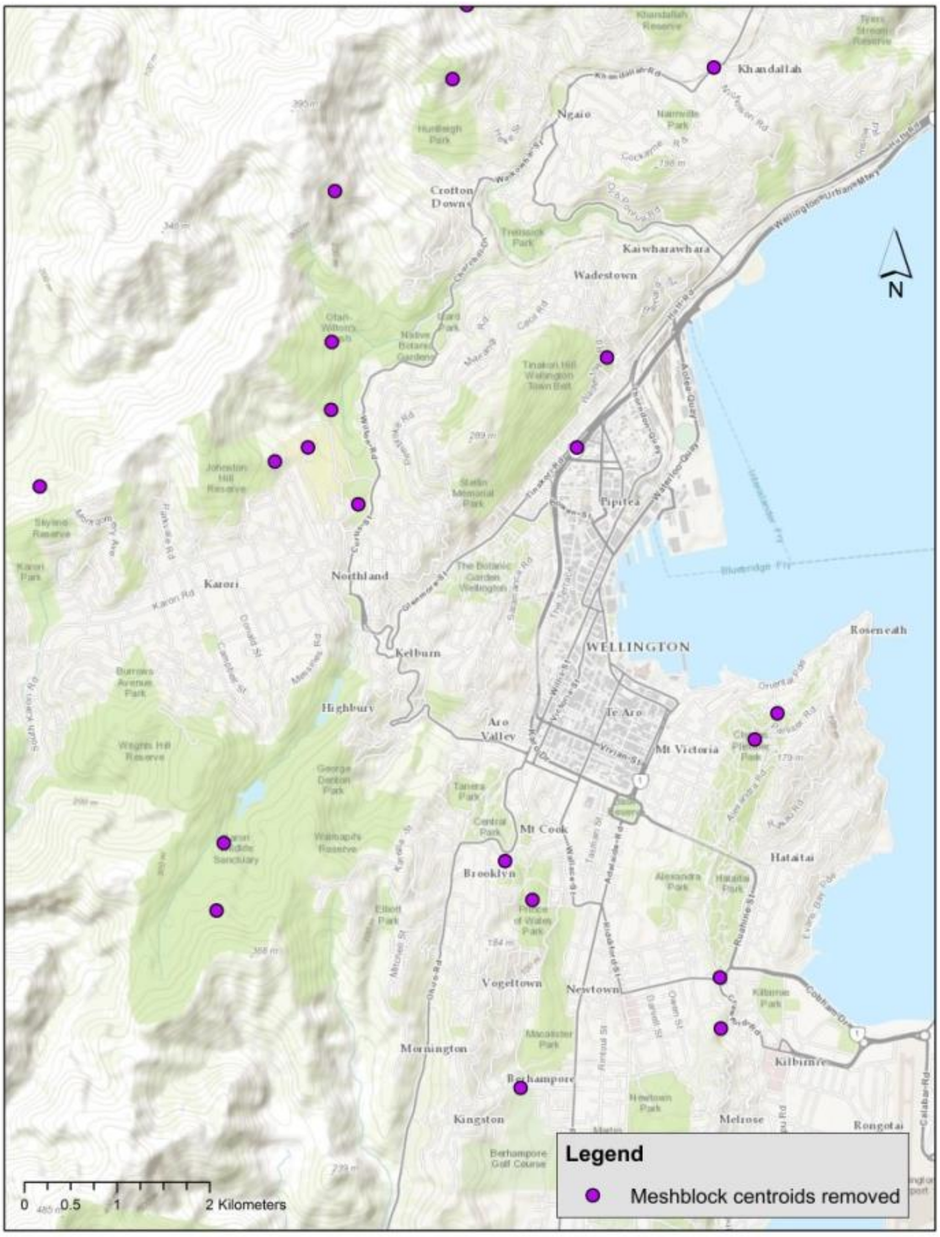


Figure 9. Map of meshblock based population weighted centroids removed as they do not represent areas where people reside or work.

3.7 Creating individual measures of the built environment

This section describes each of the components included in the Basic Walk Index (BWI) based on method 1 (standard method). Then, a description of the novel methods 2 and 3, used to create a second version of the BWI and an Enhanced Walk Index (EWI), Bike Index (BI) and Neighbourhood Destination Accessibility Index (NDAI) are given, along with a concise rationalisation of each of the measures employed. All measures were created using ESRI's ArcGIS (10.2) (Redlands, CA).

3.7.1 Standard approach, Method 1

Standard walkability indices are usually created by combining simple intensity based measures of the built environment. Originally only three components were included in the walk index: land use mix, street connectivity and dwelling density (Frank et al., 2005), however, subsequent versions included a measure of retail floor area (Leslie et al., 2007; Frank et al., 2009; Mavoa et al., 2009). Data for retail floor area was unavailable for this research and therefore only three components were used. However, previous research which tested a walk index based on three (land use mix, street connectivity, and dwelling density) versus four components (additionally including retail floor area), found that the abridged index was comparable to the four component index and had predictive validity for utilitarian walking in urban areas (Mayne et al., 2013). The simple intensity BWI created in this research was comprised of measures of land use mix, street connectivity and dwelling density and based on the methods described by Leslie et al., (2007), Mavoa et al., (2009) and Mayne et al., (2013). The following section describes the steps taken to create the BWI based on method 1. A description of the individual measures is then provided.

Steps taken to create BWI based on method 1

The steps taken to create the BWI based on method 1 are as follows:

1) each of the vector based (polygon and line) components, land use mix, street connectivity and dwelling density were created separately using standard methods (simple intensity);
2) network buffers were created at 800m, 1600m and 2400m around meshblock based PWCs, representing different neighbourhood environments;
3) using the tool *Tabulate Intersect* in ArcGIS (version 10.2), each measure was intersected with the network buffers at 800m, 1600m and 2400m and dissolved based on the meshblock identifier;
4) the values of these measures, (land use mix, street connectivity and dwelling density), at each spatial level, were standardised into deciles before being combined into a composite walk index (BWI);

5) the three measures were summed together at each spatial level, similar to previous research by Leslie et al., (2007) and Mavoa et al., (2009). The BWI created using this method will be referred to as method 1 for the remainder of this thesis.

Figure 10 presents a schema of the BWI based on method 1 (steps 1-5). The following section gives a brief rationale for including each of these measures and a description of how the simple intensity methods for each measure was derived. Each of these measures is then mapped in order to visualise their distribution for Wellington City. A summary table of the objective methods and data sources for each measure is provided in Table 3.

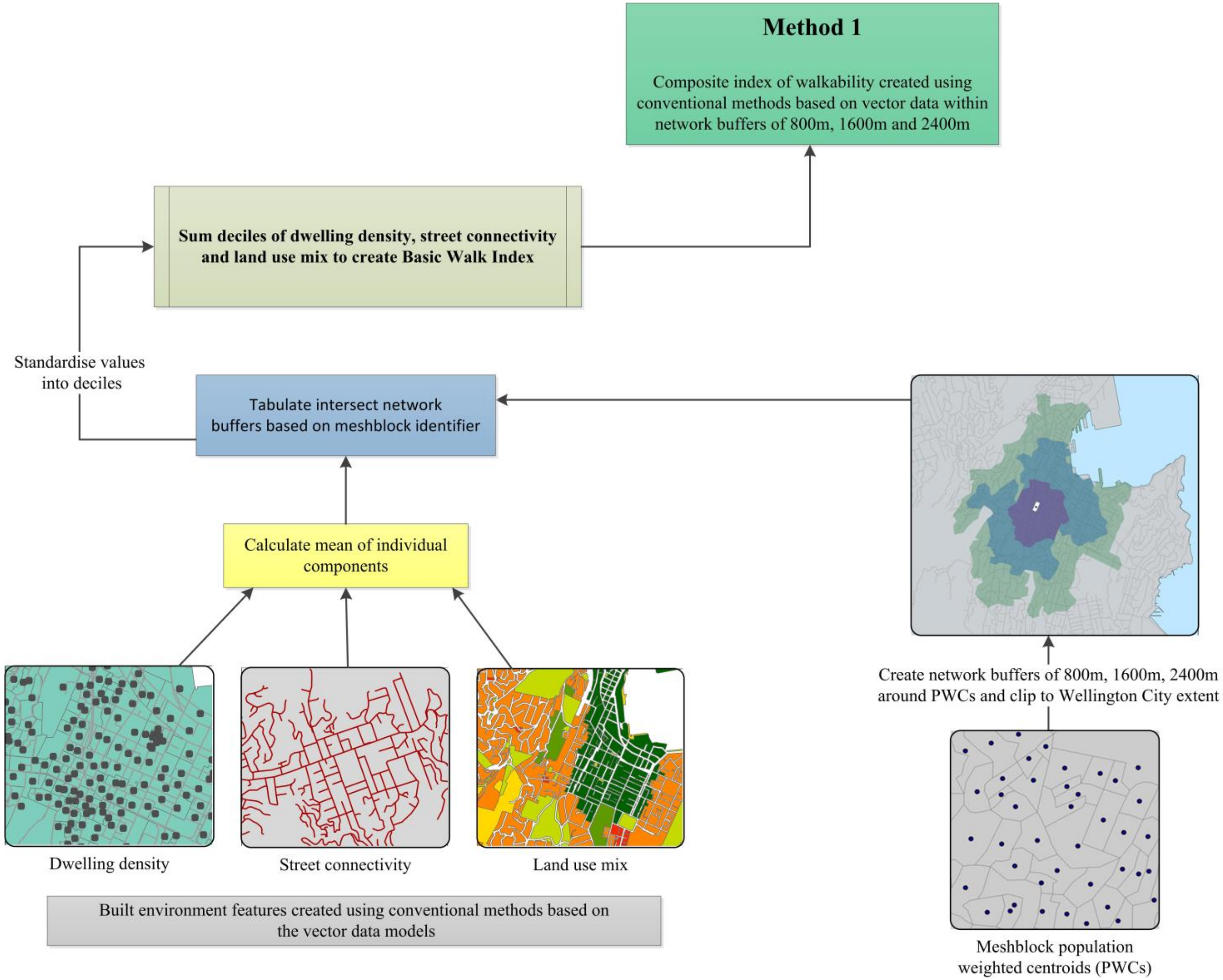


Figure 10. Schema of method 1 used to create the standard Basic Walk Index using network defined neighbourhoods at 800m, 1600m and 2400m from the meshblock population weighted centroid.

3.7.1.1 Land use mix

A greater mix of land uses has been shown to support active transport, physical activity behaviours and healthier BMIs through accounting for different accessible destinations encountered in everyday life (Saelens and Handy 2008; Li et al., 2008). Land use mix is regularly included in indices of walkability and associated with active transport modes, physical activity and lower BMI (Frank et al., 2005; Frank et al., 2010; Sallis et al., 2009; Van Dyck et al., 2010; Freeman et al., 2013; Mayne et al., 2013).

Land use and zoning data obtained from Wellington City Council (2014), (Table 3), were used to calculate the presence or absence of six land use categories: commercial, residential, retail/industrial, institutional, open space and other (e.g. vacant land) within each meshblock area unit. The land use mix was calculated using an entropy index similar to Leslie et al., (2007) and Mavoa et al., (2009). The following formula was used to calculate the land use mix score: the sum of meshblock land area was used, where *k* is the category of land uses; *p* is the proportion of land area attributed to a specific use; *N* is the number of land use categories (Equation 1; Leslie et al., 2007).

$$\text{Entropy index} = \frac{-\sum_k (p_k \ln p_k)}{\text{Ln } N} \qquad (1)$$

The entropy calculation results in values ranging from 0, indicating homogeneous land uses, to values closer to 1 indicating greater heterogeneity of land uses. These values were standardised to deciles in order to visualise how land use mix is represented at the meshblock area unit in Wellington City (Figure 11). Values close to 1 indicate low land use mix, (not very accessible or interesting destinations for walking or cycling) while values close to 10 indicate high land use mix (highly accessible and interesting destinations supportive of walking or cycling). The map (Figure 11) shows that the area around the city centre has a low mix of land uses, which could reflect the zoning of only a few land areas such as residential, retail/industrial and commercial. Areas to north, south and west of the city have larger meshblock area units and higher land use mix. This measure was included in the Basic Walk Index ((BWI based on method 1) and investigated for associations with active transport, physical activity behaviours and health outcomes in Chapters 6 and 7.

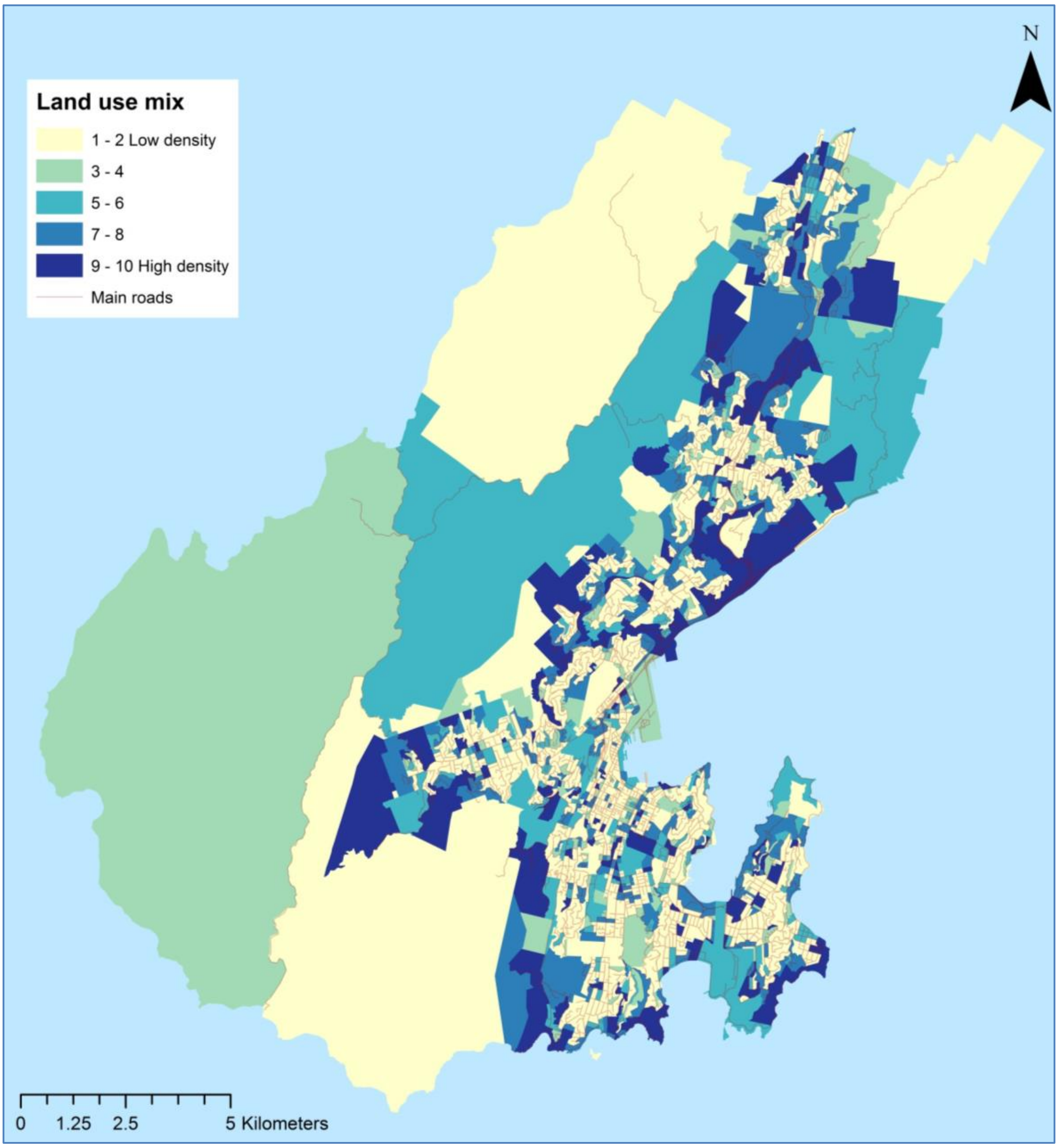


Figure 11. Vector (polygon) data map of land use mix in Wellington City by meshblock area unit.

3.7.1.2 Street connectivity

Street connectivity is commonly included in walkability indices and regularly associated with active transport, physical activity and low BMI (Frank et al., 2005; Frank et al., 2010; Mavoa et al., 2009; Sallis et al., 2009; Van Dyck et al., 2010; Freeman et al., 2013; Mayne et al., 2013). Streets that are well-connected are hypothesised to positively influence physical activity behaviours. Previous research in New Zealand (Witten et al., 2012) found positive associations between high street connectivity (intersections with 3 or more roads) and self-reported and accelerometer-derived measures of physical activity.

The street connectivity measure derived for Wellington City as part of this research utilised a road layer, obtained from Land Information New Zealand (LINZ). The method frequently used in the literature and replicated in this research was estimated by calculating intersection density of three or more unique intersecting streets (Leslie et al., 2007; Mavoa et al., 2009). Similar to Mavoa et al., (2009), to ensure street intersections that coincided with meshblock boundaries were included, a buffer of 20 meters around each meshblock boundary was created. Intersection density was calculated as the number of intersections per square kilometre within the meshblock buffer, including intersections with 3 or more roads (Mavoa et al., 2009) (Equation 2).

$$\text{Street connectivity} = \frac{\text{number of intersections}}{\text{area}} \qquad (2)$$

Values were standardised to deciles and mapped, in order to visualise the measure of street connectivity at the meshblock area unit (Figure 12). Values close to 1 indicate low street connectivity (not conducive to walking or cycling) and values close to 10 indicate high street connectivity (very conducive to walking and cycling). The map (Figure 12) shows high density of street connectivity in the city centre and low street connectivity in areas to the west and north of the city centre. This measure was also included in the BWI (method 1) and investigated with active transport, physical activity and health outcomes in Chapters 6 and 7.

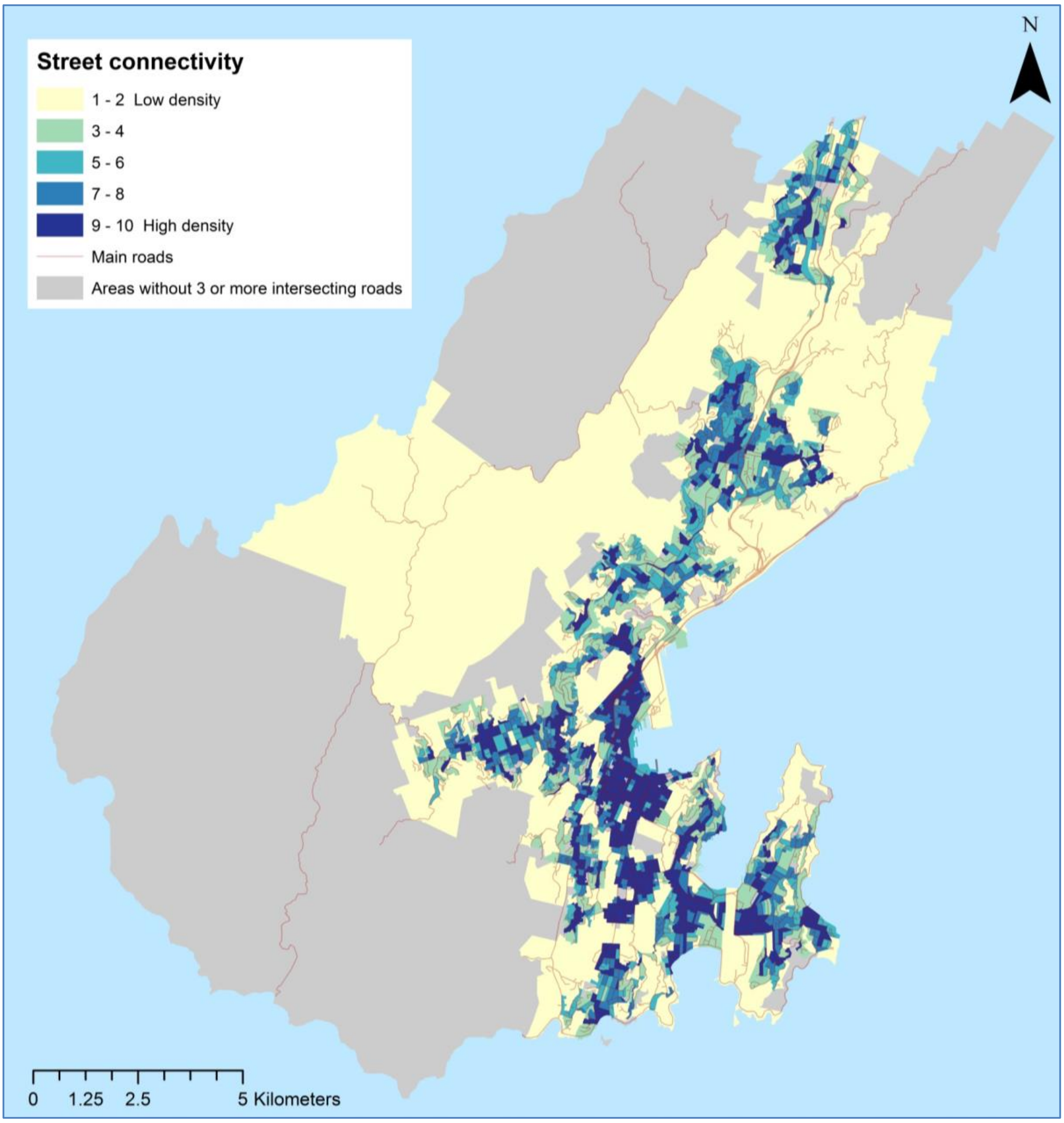


Figure 12. Vector (polygon) data map of street connectivity in Wellington City by meshblock area unit.

3.7.1.3 Dwelling density

Dwelling density is a measure regularly included in walkability indices and associated with active transport, physical activity and low BMI (Frank et al., 2005; Frank et al, 2010; Mavoa et al., 2009; Sallis et al., 2009; Van Dyck et al., 2010; Glazier et al., 2012; Freeman et al., 2013; Mayne et al., 2013). A number of studies have reported a positive association between dwelling density and walking and biking, (Carr, Dunsiger, and Marcus, 2010; Forsyth et al., 2008; Witten et al., 2012). It is hypothesised that areas where there are high volumes of housing and thus residents, there are destinations such as shops and services closer together encouraging active transport and physical activity behaviours (Sallis et al., 2012).

Dwelling density was calculated using meshblock data containing the count of occupied private dwellings taken from the New Zealand 2013 Census (Statistics New Zealand, 2014). The area of private residential land was also provided by the Census 2013 and the dwelling density was calculated by dividing the count of dwellings by the residential area of land for each meshblock (Equation 3).

$$\text{Dwelling density} = \frac{\text{Count of private dwellings in each meshblock}}{\text{residential area of land in each meshblock}} \qquad (3)$$

Values were standardised to deciles and mapped in order to visualise dwelling density for Wellington City (Figure 13). Values close to 1 indicate low dwelling density and values close to 10 indicate high dwelling density. Areas adjacent to the city centre have high density of dwellings, whereas areas previously identified in Figure 9 as parks and hills, have low dwelling density (Figure 13). This measure was included in the BWI (method 1) and investigated for associations with active transport, physical activity and health outcomes in Chapters 6 and 7.

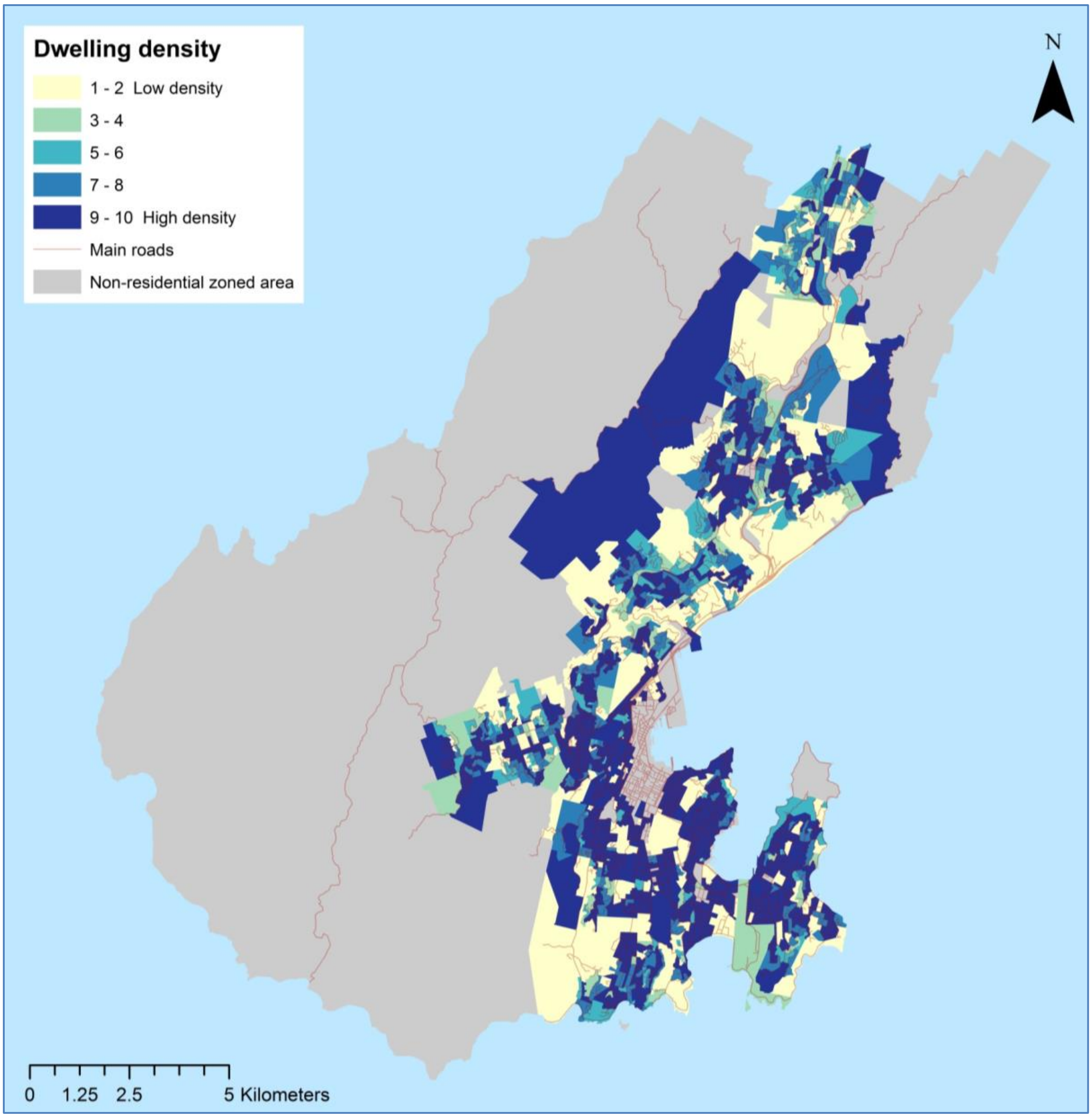


Figure 13. Vector (polygon) data map of dwelling density in Wellington City by meshblock area unit.

Table 3. Summary table of built environment measures, data sources and methods.

Method 1- Basic Walk Index data sources and methods				
Measure	**Database**	**Data source**	**Year**	**GIS-methods**
Land use mix	Zone areas	Wellington City Council	2014	An entropy index was calculated for Wellington City. The presence or absence of six types of land use, commercial, retail/industrial, open space, institutional, other, residential were included in the measure. The level of heterogeneity of land uses was calculated, based on the meshblock identifier, and ranged on a scale from 0, (homogenous) to 1 (heterogeneous).
Street connectivity	Road centre line	Land Information New Zealand (LINZ)	2015	Intersection density was calculated as the number of intersections with greater than 3 intersecting roads per square kilometre in each meshblock.
Dwelling density	New Zealand Census	Statistics New Zealand	2013	Dwelling density was calculated as the number of dwellings divided by the residential land area in each meshblock.

3.7.2 Novel approach, Methods 2 and 3

After identifying limitations to the standard simple intensity based method, an alternative method, kernel density estimation (KDE) was utilised to create individual and composite measures of the built environment for walking, cycling and neighbourhood destination accessibility. KDE is a relatively new and underutilised method to measure the built environment in relation to active transport and physical activity behaviours. As mentioned in Chapter 2, section 2.6.3, previous research has used KDE to measure crime hotspots, (Chainey, 2013; Hart and Zandbergen, 2014), food outlets (Thornton et al., 2012; Rundle et al., 2007; Bader et al., 2010) and less commonly greenspace and recreation (Maroko, 2009), recreational resources (Diez-Roux et al., 2007) and neighbourhood destinations (King et al., 2015). To the author's knowledge, only recent research by Buck et al., (2015a; 2015b) have used KDE to measure the built environment and test associations with physical activity in children. This thesis research aims to address this gap by creating novel (KDE, with a vector component-buffers) built environment measures for walking, cycling and neighbourhood destination accessibility and test associations with active transport, physical activity and health outcomes in adults in New Zealand. The following section describes the steps taken to create each of the individual measures using the novel method.

Steps taken to create methods 2 and 3

Numerous models were created using Model Builder in ArcGIS (version 10.2), to automate and iterate through every process described below. The steps taken in all of the individual components of the built environment were as follows:

1. Kernel densities were created for the individual measures based on a fixed bandwidth of 500m (Buck et al.,2015b) and raster cells of 10mx10m using the *Spatial Analyst* tool, *Kernel Density*
2. Cells that contained no data were removed using the tool *Set Null*
3. The analysis tool *Slice*, was used to split the range of KDE raster values into deciles of equal area in order to standardise for comparability in the analysis
4. Two types of buffers were created at three levels of geography, 800m, 1600m and 2400m
    - Method 2: Euclidean buffers at 800m, 1600m and 2400m were created around meshblock based PWCs using the *Buffer* tool from the proximity toolset.
    - Method 3: Network buffers at 800m, 1600m and 2400m were created around meshblock based PWCs by generating network service areas with the *Network Analyst extension.*
5. Buffers were clipped to the Wellington City extent (Wellington Territorial Authority boundary) using the *Clip* tool from the extract toolset, in order to exclude areas calculated beyond the boundary such as the ocean
6. Individual measures were summed to create indices of the built environment using the tool *Cell Statistics*.
7. The mean and median kernel density values of each individual and composite index of the built environment were calculated within the Euclidean (method 2) and network buffers (method 3), based on the meshblock identifier, using the tool *Zonal Statistics as Table.*

Figure 14 presents a schema of the steps taken to create the novel KDE and vector (Euclidean and network buffers) based measures for methods 2 and 3 (steps 1-7). The following section describes each measure that was included in the Basic Walk Indices (BWIs), Enhanced Walk Indices (EWIs), Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs), based on methods 2 and 3. Raster maps are presented for each measure to illustrate their spatial and proximal density. This is followed by a description of the method of standardisation and explanation of how each measure was combined into indices of walkability, bikeability and destination accessibility.

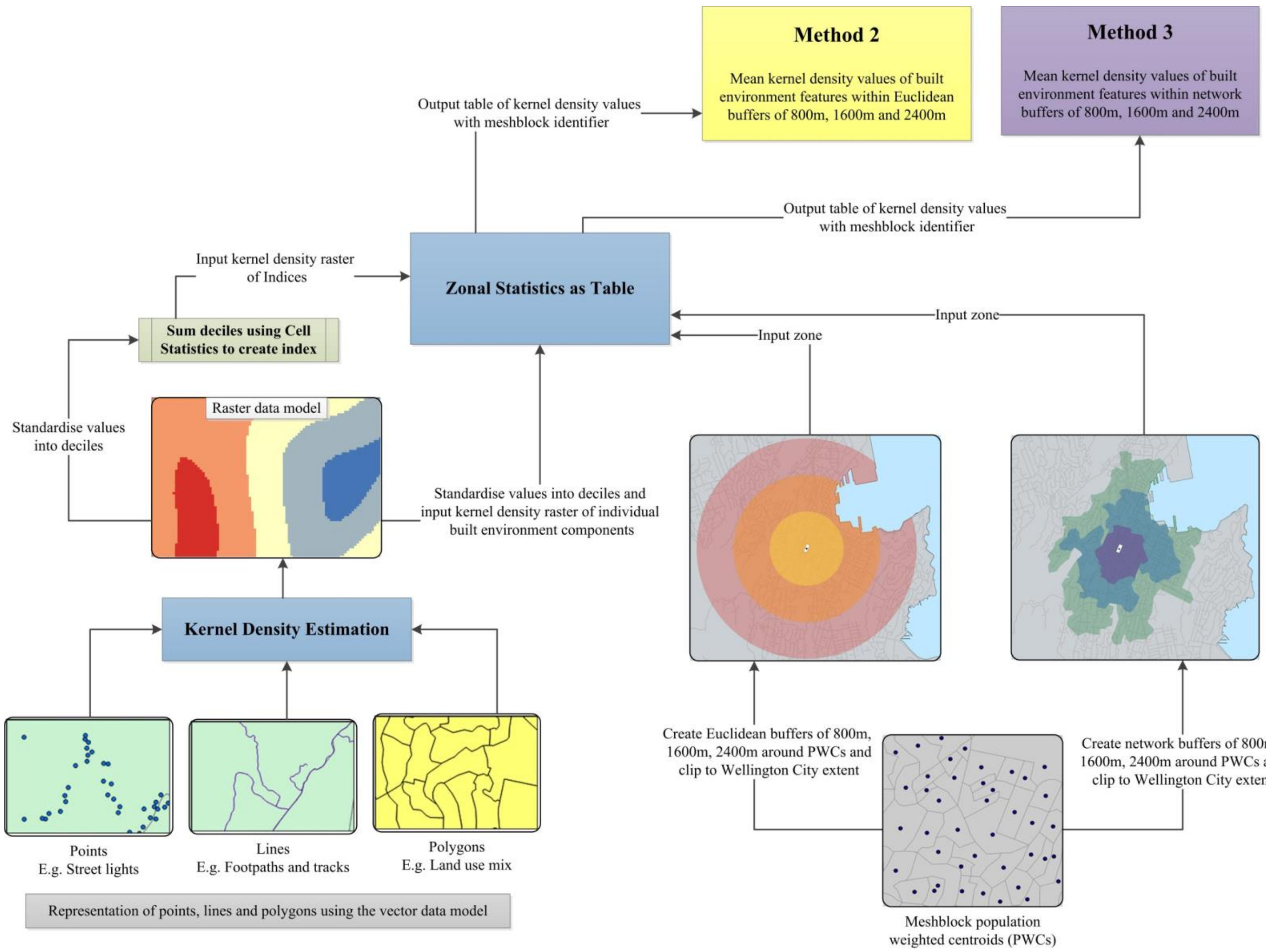


Figure 14. Schema of methods 2 and 3 used to calculate the mean and median values of built environment measures calculated within the Euclidean and network buffers based on the meshblock identifier.

3.7.2.1 Land use mix

As described in the previous section 3.7.1.1, land use mix is regularly included in walkability indices of the built environment (Frank et al., 2005; Frank et al., 2010; Sallis et al., 2009; Van Dyck et al., 2010; Freeman et al., 2013; Mayne et al., 2013). However, few studies have used KDE to measure land use mix in urban areas. The next section describes the steps take to create a more nuanced measure of land use mix based on the novel method.

A 100m raster grid was created and clipped to the Wellington City extent. The clipped polygon grid was converted to points and 500m Euclidean buffers were created around the point grid. The vector based polygon land zone data was categorised into six land uses, commercial, residential, retail/industrial, institutional, open space and other (e.g. vacant land). The tool *tabulate intersection* was used to compute the intersection between the 500m buffers and land zone data and cross-tabulated the area, length and count of the intersecting features. The tabulated table was joined to the point grid layer and hectare values were converted to percentages of land use area. Similar to Mavoa et al., (2009), the entropy index was calculated based on the percentage of each land use in the buffers. Values close to 1 indicated heterogeneous land uses and values close to 0 indicated homogenous land uses. These values were used to compute KDE creating a smoothed continuous surface of mixed land use for Wellington City. Steps 1-7 described at the beginning of section 3.6.2 were completed to create a measure of land use mix based on methods 2 (Euclidean) and 3 (network buffers). This measure is an example of a more nuanced way of calculating land use mix at a fine grained spatial level, rather than the meshblock area level and deriving the mean density of land use within Euclidean and network buffers. A map of land use mix density is presented as a continuous kernel density surface in Figure 15. Values close to 10 in dark blue colour indicate areas of high density and proximity of land uses. In contrast to the simple intensity measure of land use mix (method 1), the city centre has high density of land uses (dark blue). This novel measure of land use mix is included in the BWIs, EWIs and BIs.

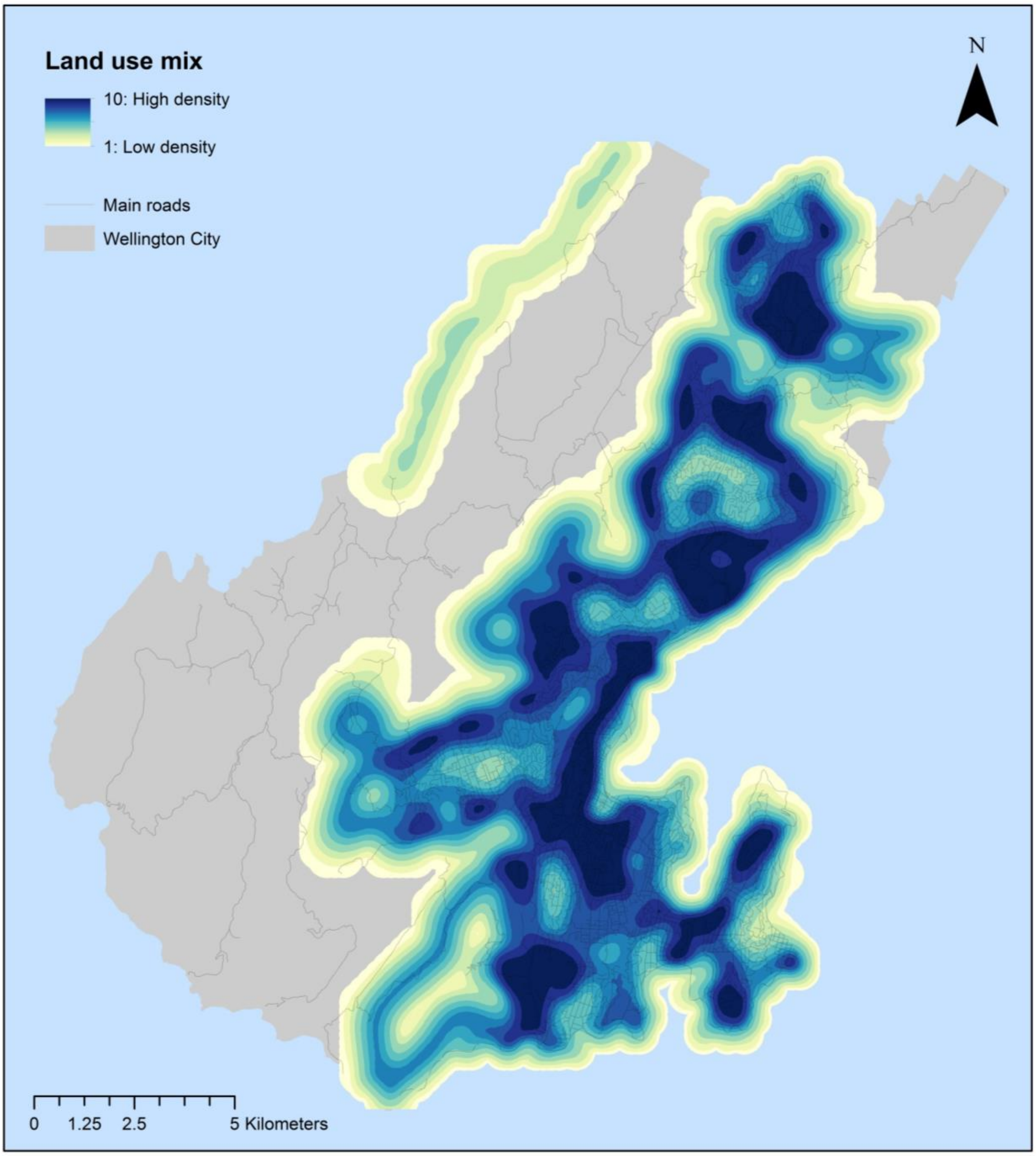


Figure 15. Kernel density estimation of land use mix in Wellington City.

3.7.2.2 Street connectivity

As described previously in section 3.7.1.2, measures of street connectivity are regularly included in analyses of the built environment, active transport, physical activity and health outcomes (Frank et al., 2005; Frank et al., 2010; Mavoa et al., 2009; Sallis et al., 2009; Van Dyck et al., 2010; Freeman et al., 2013; Mayne et al., 2013). Well-connected streets provide opportunities for individuals to walk or cycle short distances to neighbourhood destinations. The measure created for inclusion in the novel BWI, EWI and Bike Index (BI) is based on road valency. Valency refers to the number of arcs converging at a point, when applied to a road network it refers to the number of roads converging at an intersection or node. Roads containing a valency of three or more were considered to reflect high connectivity. The final value was computed using the *kernel density* tool and used to create a continuous KDE of street connectivity for Wellington City. Steps 1-7, described in section 3.6.2, were taken to create methods 2 and 3. The KDE of street connectivity was standardised into deciles in order to include the measure in the BWIs, EWIs and BIs. A map of the measure is presented to visualise the spatial intensity and proximity of street connectivity in Wellington City (Figure 16). Values close to 10, in dark blue colours, indicate higher density of street connectivity which coincides with Wellington City centre. Roads to the west of the city have low density of street connectivity.

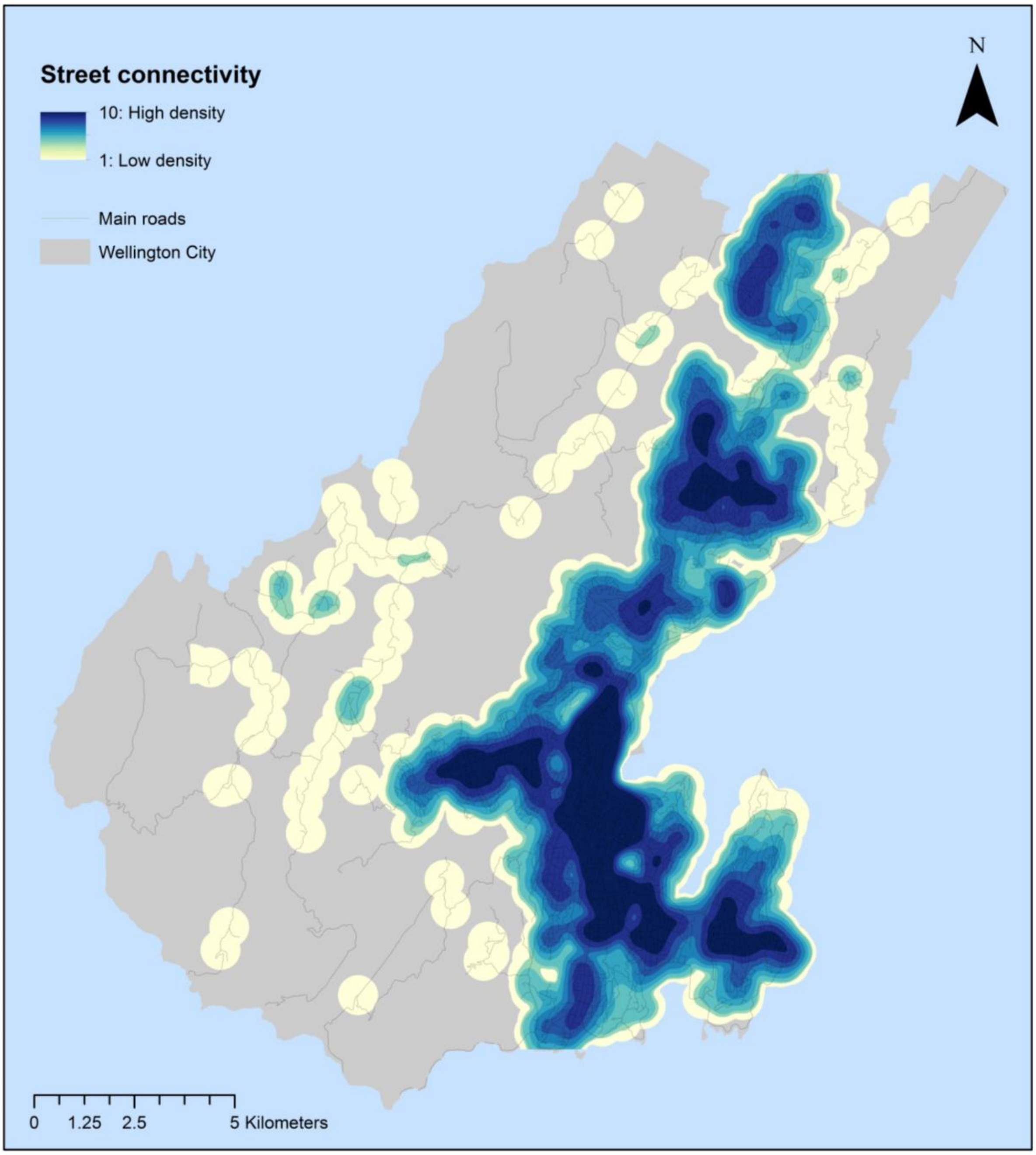


Figure 16. Kernel density estimation of street connectivity for Wellington City, with the highest density concentrated in the city centre.

3.7.2.3 Dwelling density

As described in section 3.7.1.3, dwelling density is commonly included in walkability indices and associated with active transport, physical activity and health outcomes (Frank et al., 2005; Frank et al, 2010; Mavoa et al., 2009; Sallis et al., 2009; Van Dyck et al., 2010; Freeman et al., 2013; Mayne et al., 2013). Areas with high density of dwellings also tend to have destinations such as services and shops close by, encouraging active transport and physical activity behaviours (Sallis et al., 2009). The dwelling density measure was calculated based on the count of private dwellings in each meshblock. These values were computed into the *kernel density tool* and used to create a continuous surface of residential density for Wellington City. Steps 1-7 (section 3.6.2), were completed to create methods 2 and 3. Values were standardised to deciles and included in the BWIs and EWIs. A map of Wellington City, representing the density and proximity of dwellings is presented in Figure 17. Values close to 10 indicate high density of dwellings. Similar to street connectivity, there is a high density of dwellings located in the city centre.

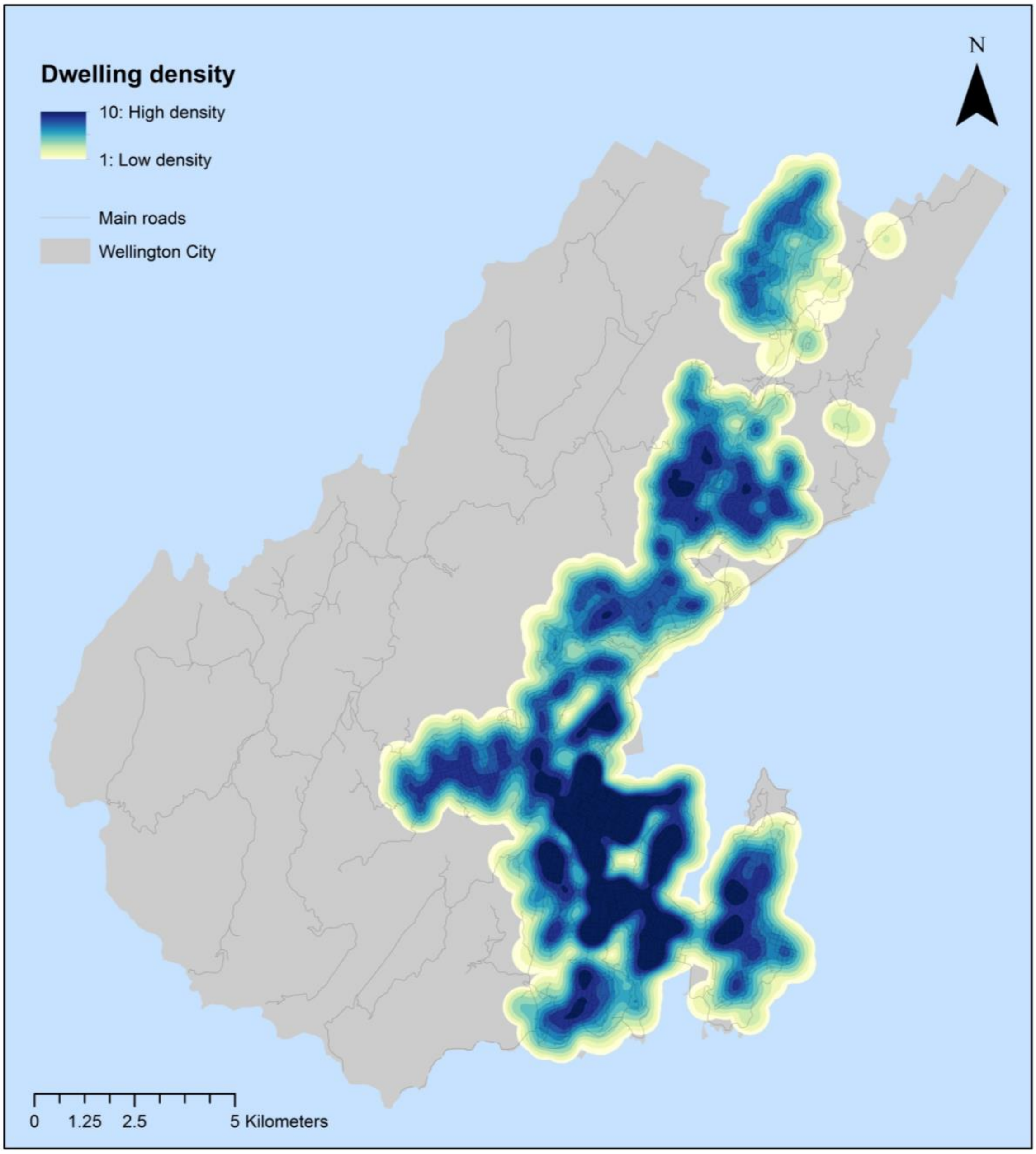


Figure 17. Kernel density estimation of dwelling density for Wellington City, with the highest density concentrated in the city centre.

3.7.2.4 Footpaths and tracks

The most common method of assessing footpaths in the literature is through subjective measurement. Many of the studies assessed footpaths in terms of functionality and quality, based on perceptions of individuals using them (De Bourdeaudhuij et al., 2003; Giles-Corti and Donovan, 2002; Duncan and Mummery, 2005). Duncan and Mummery (2005) found that Euclidean distance to the footpath network and perceptions of footpaths were significantly associated with the likelihood of recreational walking. Including footpaths and tracks in a walkability index is important as pedestrians do not necessarily walk along streets and potentially take advantage of cut through between buildings, parks and alleyways. Including an objective measurement of footpaths and tracks to the Enhanced Walk Index (EWI), adds additional detail of the influence of the built environment on active transport and physical activity behaviours.

Polyline data of footpaths were obtained from Wellington City Council and combined with track data from Land Information New Zealand (LINZ) (Table 4). In order to capture tracks and cut-through in parks and side streets, all tracks that were classified as vehicle access were removed, while all tracks assigned to walking were kept. The two datasets were combined using a spatial join. A value of 1, representing the presence of footpaths and tracks was used to compute the KDE measure. Steps 1-7 (section 3.6.2), were completed to create methods 2 and 3. The resulting values were standardised to deciles and included in the EWI. Figure 18 gives an idea of the density of footpaths and tracks in the Wellington Region. It is useful to note, this measure captures some of the great walking tracks such as the Skyline walkway in the middle of the map and captures tracks and alleyways not included in the street connectivity measure.

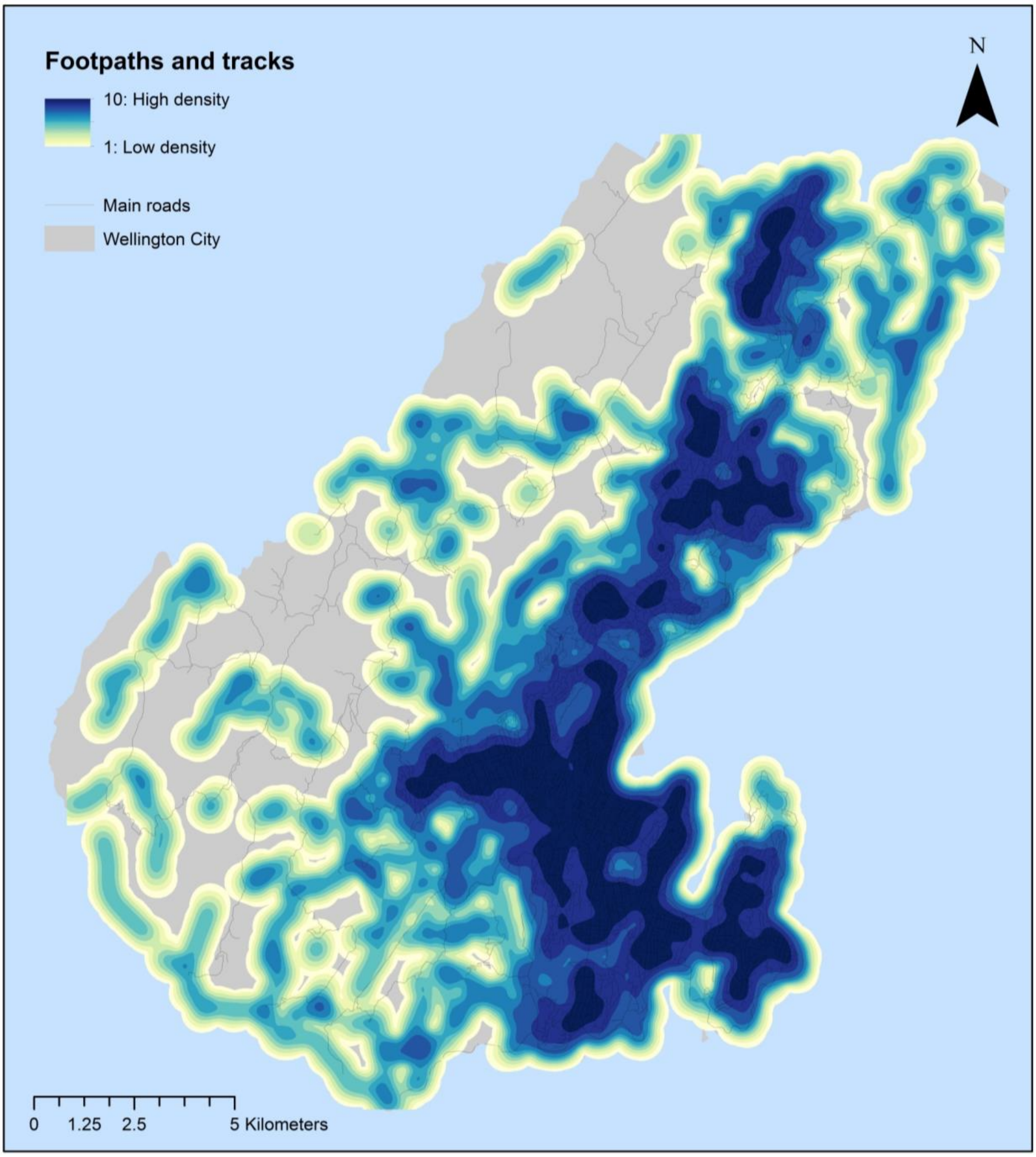


Figure 18. Kernel density estimation of footpaths and tracks in Wellington City.

3.7.2.5 Street lights

In relation to the built environment and physical activity, street lights are less frequently measured using objective measures in GIS (Brownson et al., 2009). They are more commonly measured using subjective self-reports, where the presence of street lights is examined in relation to perceptions of safety. However a couple of studies did use objective measurement methods to capture street light density, for example, the total amount of roadway within 20m of street lights within a set radii, (Duncan and Mummery, 2005) and the number of street lights per length of road (Forsyth et al., 2008). Through their examination of environmental factors associated with physical activity, Duncan and Mummery, (2005) found no association between subjective self-reported presence of street lights and physical activity. Whereas Forsyth et al., (2008) found total walking in mean miles per day to be positively correlated with sidewalks and street lights. While walking for transport was positively correlated, walking for leisure was negatively correlated with street lights. Other research by Troped et al., (2003) found the presence of street lights was also positively associated with transport related physical activity. In relation to cycling, Titze et al., (2008) found that 60 percent of cyclists preferred the presence of street lights while cycling at night.

Much of the literature on the subjective measures of the built environment includes street lights as a potential predictor of physical activity. However, completing a subjective study is beyond the scope of this research and previous research has found associations with objective measures of street lights, active transport and physical activity. Therefore, an objective measure of street lights was included in this research as a proxy for safety. Point data was obtained from Wellington City Council of all the street lights in Wellington City. Each point was given a value of 1 and computed into the *kernel density tool*. Steps 1-7, described at the beginning of section 3.6.2 were completed to create methods 2 and 3. Values were standardised to deciles and included in the EWIs and BIs. A map of the density and proximity of street lights in Wellington City is presented in Figure 19. Values close to 10 indicate high density of street lights. Similar to dwelling density, there is a high concentration of street lights in the city centre.

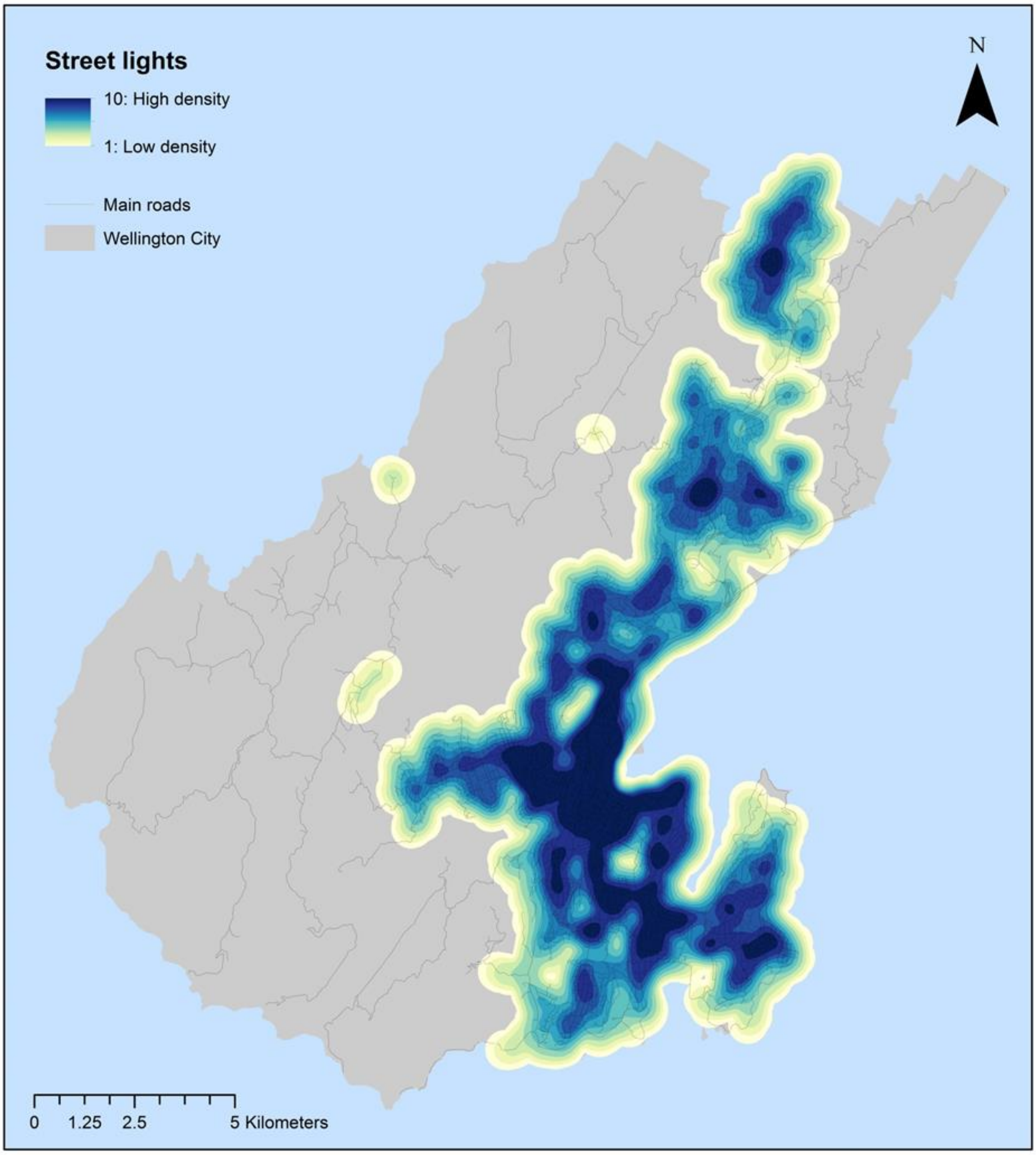


Figure 19. Kernel density estimation of street lights in Wellington City.

3.7.2.6 Slope

The justification for using slope is based on the assumption that topography affects whether people walk or cycle. Previous research on the walkability of the built environment does not frequently use slope as a possible attribute. For the studies that did include slope (Winter et al., 2010), it was found to be highly correlated with cycling. Winters et al., (2010) used a measure of hilliness where they calculated the average slope of the digital elevation model (DEM) in a neighbourhood. McGinn et al., (2007) created a slope with a cut off of ≥ 8 degrees, where any road over 8 degrees was classified as unwalkable. They calculated the slope for 100m segments along the road network.

Drawing from McGinn et al.'s (2007) method a number of steps were taken in ArcGIS (version 10.2) to create a more nuanced measure of slope. They are as follows, 1) the road network for Wellington City was dissolved into one line; 2) using the command c*reate points on line* (obtained from Ianbroad.com, GIS expert, provides tools online), points were created every 100m distance from the start to the end of the line; 3) the tool *split line at point* was used to create 100m road segments; Note: some roads had dangles shorter than 100m and after visual screening of the location of the roads, roads segments down to a 50m cut off length were included, using roads less than 50m would create spikes of slope between two short points. This process accounted for most of the roads in Wellington City. 4) the tool *feature vertices to points* was used to determine the points at the start and the end of each 100m road segment; 5) a new columns in both the start and end point files were created, called start_id and end_id; 6) using the tool *extract values to points* the slope values (from the digital elevation model; DEM) were extracted at the start and end points of the road segment; 7) a new column in both the start and end point files was created, called start_elevation and end_elevation and used calculate field to input the raster values into these columns; 8) the *join field* tool was used to join the start and end elevations to the original 100m road segments; 9) in the attribute table of the 100m road segment file, add field was used to create a new column titled PC_change and ([end_elevation]-[start_elevation])/[Shape_Length]) * 100 was entered in the field calculator; 10) a new column was created and any values ≥ 8 degrees were given a value of 1 and categorised as unwalkable and unbikeable. Values less than ≤ 8 degrees were given a value of 0 and categorised as walkable and bikeable. KDE was calculated based on these values. Steps 1-7, described at the beginning of section 3.6.2 were completed to create methods 2 and 3. Values were standardised to deciles and inverted whereby values close to 10 represented low density of slope ≥ 8 degrees and values close to 1 indicated high density of slope ≥ 8 degrees. This step was necessary in order to be included in the indices of walkability (EWI) and bikeability (BI). A map of the density of slope, defined as ≥ 8 degrees is presented in Figure 20. It shows there is a high concentration of slope ≥ 8 degrees in and around the city centre.

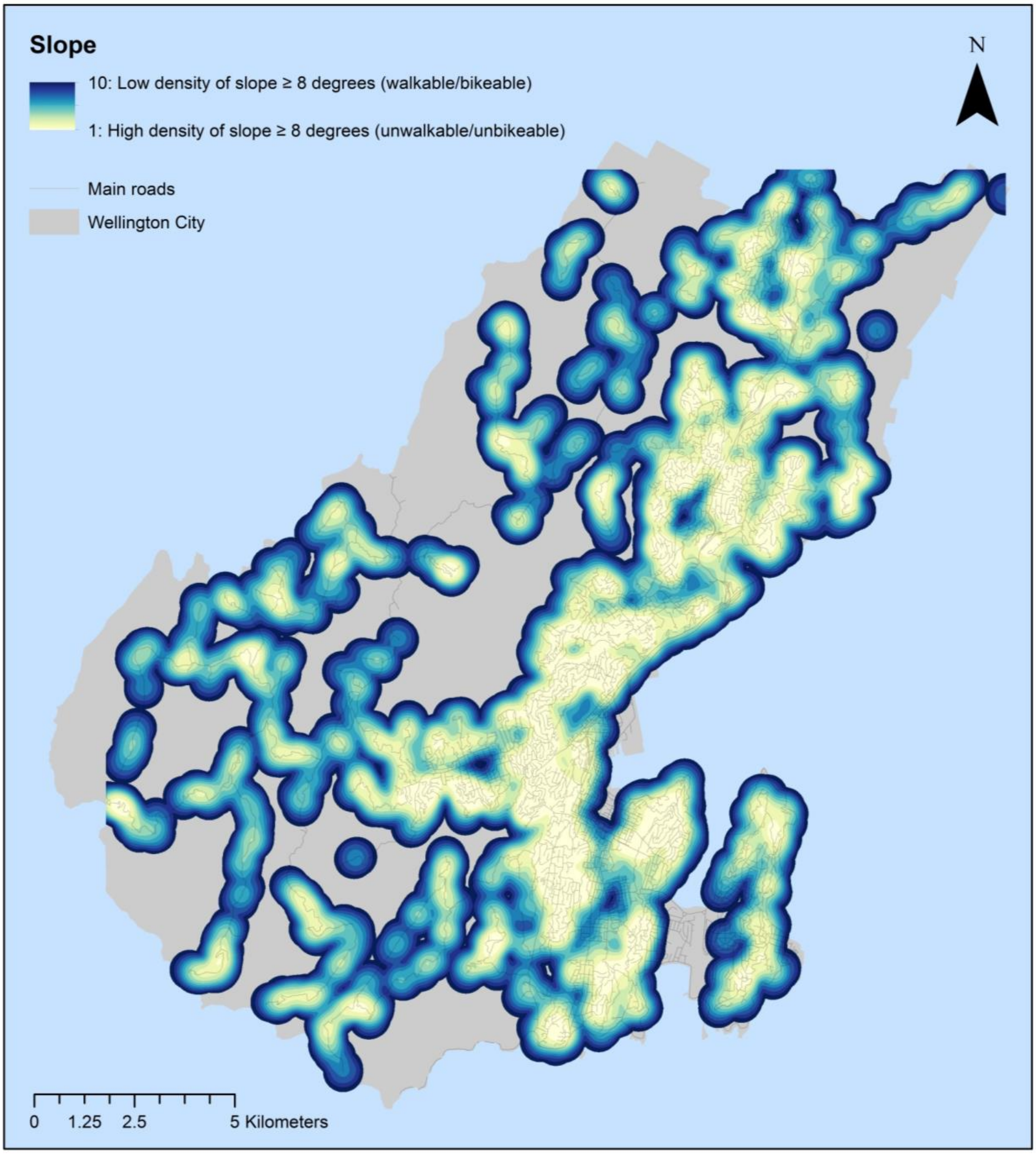


Figure 20. Kernel density of slope ≥ 8 degrees along the road for Wellington City.

3.7.2.7 Bike parking

Providing cycling facilities at the end of trips can encourage cycling behaviours. For example, previous research by Buehler, (2012) found bicycle parking was associated with higher levels of bicycle commuting. In addition, providing facilities such as sheltered bike parking and showers in the workplace can encourage cycling for transport (Wardman et al., 2007; Pucher et al., 2010). This thesis is interested in features of the built environment that could encourage cycling behaviours for transport and physical activity and thus included bike parking as one of the components in the Bike Index.

Data on bike parking was obtained from Wellington City Council, however they did not specify whether the parking was sheltered or not. Furthermore, data on showering facilities in workplaces in Wellington City was not available. The addresses of all bike parking in Wellington City were given a value of 1, representing the presence of parking. These values were used to calculate the density and proximity of bike parking based on KDE. Steps 1-7, described at the beginning of section 3.6.2 were completed to create methods 2 and 3. Values were standardised to deciles, whereby values close to 10 represented high density of bike parking and values close to 1 represented low density of bike parking. This measure of bike parking was then summed with other components of the built environment to create indices of bikeability, based on methods 2 and 3. A map of the density of bike parking in Wellington City is provided in Figure 21. Areas with high density of bike parking are concentrated in the city centre.

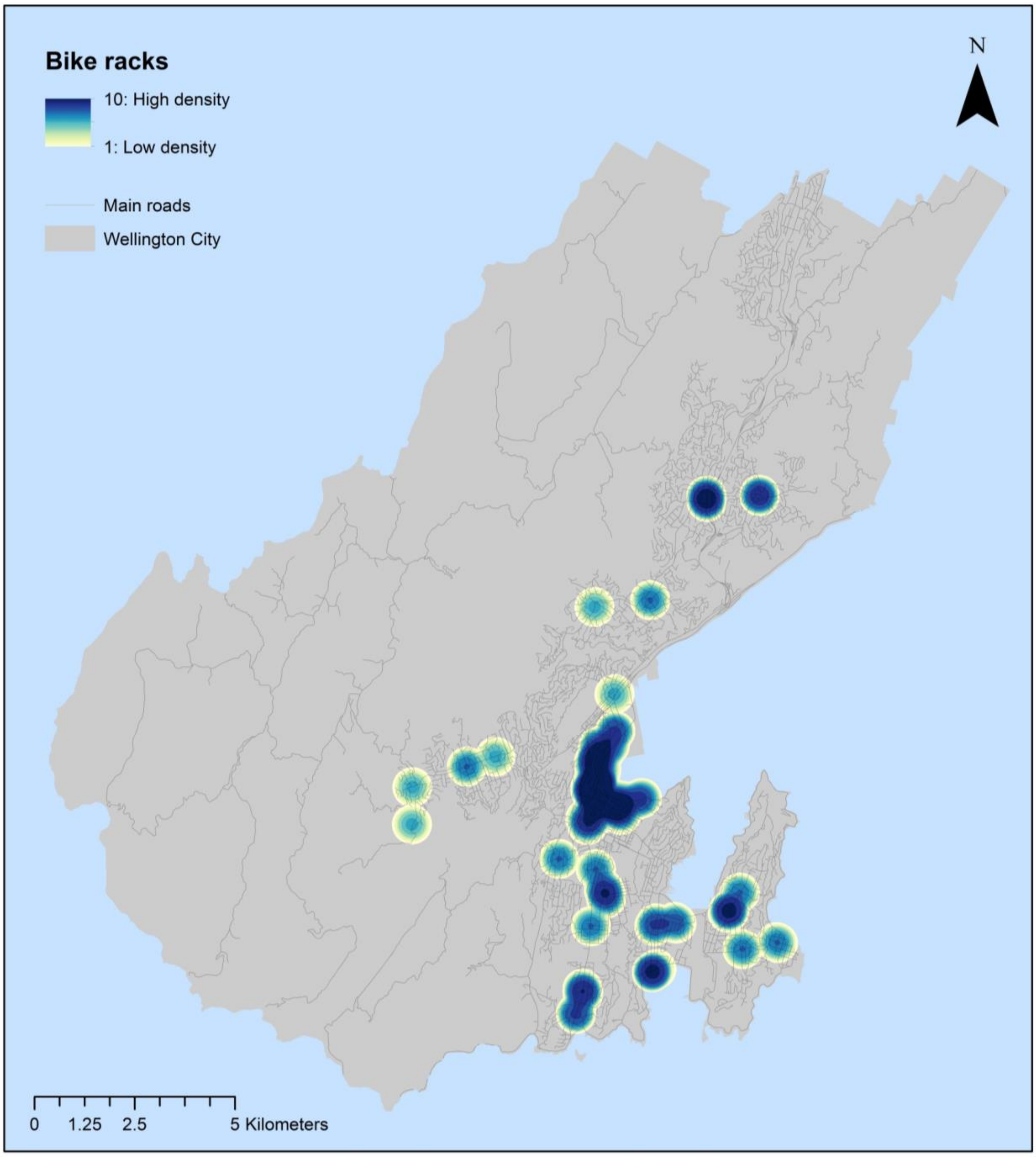


Figure 21. Kernel density map of bike parking in Wellington City.

3.7.2.8 Cycle lanes

In addition to cycling facilities, infrastructure such as cycle lanes can encourage active transport and physical activity behaviours. Cycle lanes usually include dedicated road space and are painted with cycle signs or patches of road in bright colours (Pucher et al., 2010). Cycle paths on the other hand are separated from the road and are perceived as safer for cyclists than cycling on the road (Tin Tin et al., 2009). Previous research has found a positive association between measures of cycle lanes and cycling behaviours (Dill and Voros, 2007; Pucher et al., 2010). This research is focused on features of the built environment that could facilitate and encourage cycling for transport and physical activity and thus included cycle lanes in the bikeability index.

Data on cycle lanes was obtained from Wellington City Council. The data did not specify on the type of lanes, whether separated or as part of the road. Each lane was given a value of 1 and used to compute KDE for Wellington City. Steps 1-7, described in section 3.6.2 were completed to create methods 2 and 3. Values were standardised to deciles, whereby values close to 10 represented high density of cycle lanes and values close to 1 represented low density of cycle lanes. The cycle lane measure was summed with other components of the built environment hypothesised to influence cycling behaviours. Indices of bikeability were created based on methods 2 and 3. The density and proximity of cycle lanes is presented in Figure 22. As evidenced by the map, there was a limited amount of data on cycle lanes available for Wellington City. However, the density of cycle lanes available was concentrated along the coast and city centre.

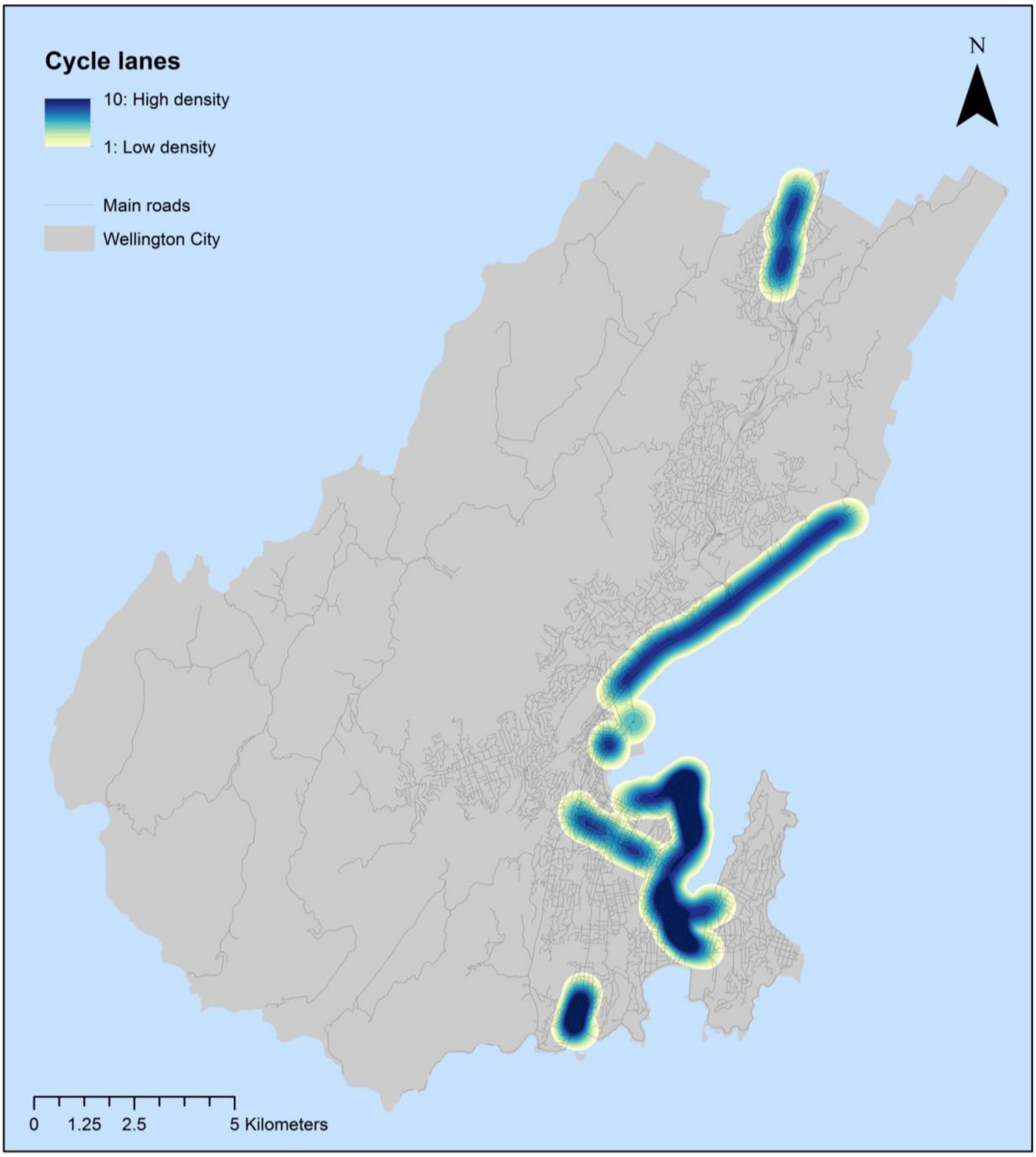


Figure 22. Kernel density map of cycle lanes in Wellington City.

3.7.2.9 Neighbourhood destinations

Destinations are frequently cited as a key component to encouraging active transport and physical activity in the neighbourhood built environment. The rationale behind the concept, is that people need destinations to walk or cycle to and certain types of destinations such as cafés, restaurants, museums and parks to name a few, are believed to encourage active transport modes and physical activity (Brownson et al., 2009; Witten et al., 2011; King et al., 2015).

The index created as part of this research is an alternative version of the Neighbourhood Destination Accessibility Index (NDAI) created by Witten et al., (2011). The aim of their index was to provide a composite measure of pedestrian access to various destinations in the built environment. They used eight domains of neighbourhood destinations, education, transport, recreation, social and cultural, food retail, financial, and health and other retail, to create an NDAI for all four New Zealand cities. Their method was based on the simple intensity approach, the alternative NDAI developed as part of this research was based on the novel KDE (with a vector component- buffers) method.

A list of destinations in Wellington City, sourced free from zenbu.co.nz, Ministry of Education, Ministry of Health and LINZ, was used to collate all the addresses for each destination (data entries ranged from October 2006-June 2014, Table 4). Seven domains (28 amenities in total) were collated and geocoded to point data. In contrast with Witten et al., (2011), the recreation domain included accessible greenspace and sports facilities only, accessible beaches were not included. The greenspace layer was provided as vector polygon data, therefore a method similar to the one utilised for the land use mix measure (section 3.6.2.1) was completed. A 100m raster grid was created and clipped to the Wellington City extent and 500m Euclidean buffers were created around a point grid. The tool *tabulate intersection* was used to compute the intersection between the 500m buffers and greenspace data and the area of the intersecting features was cross-tabulated. The proportion of greenspace within each buffer was then calculated and joined to the point grid. Witten et al., (2011) included weights for each of the eight domains to represent the relative importance of each destination as an incentive for physical activity. These weights were applied to the point values of the eight destination domains (including greenspace) and KDE was used to calculate the density and proximity of these destinations across a continuous map surface. Similar to the previous individual measures, steps 1-7 described at the beginning of section 3.6.2, were completed for education, recreation (including greenspace), transport, social and cultural, food retail, financial, health and other retail destination domains. These individual raster's were standardised to deciles and summed together to form an index of neighbourhood destination accessibility (NDAI) based on methods 2 and 3.

A KDE map of the NDAI is provided in Figure 23. High density of destinations is clustered in the city centre with pockets of high destinations in areas to the north, south and east of the city.

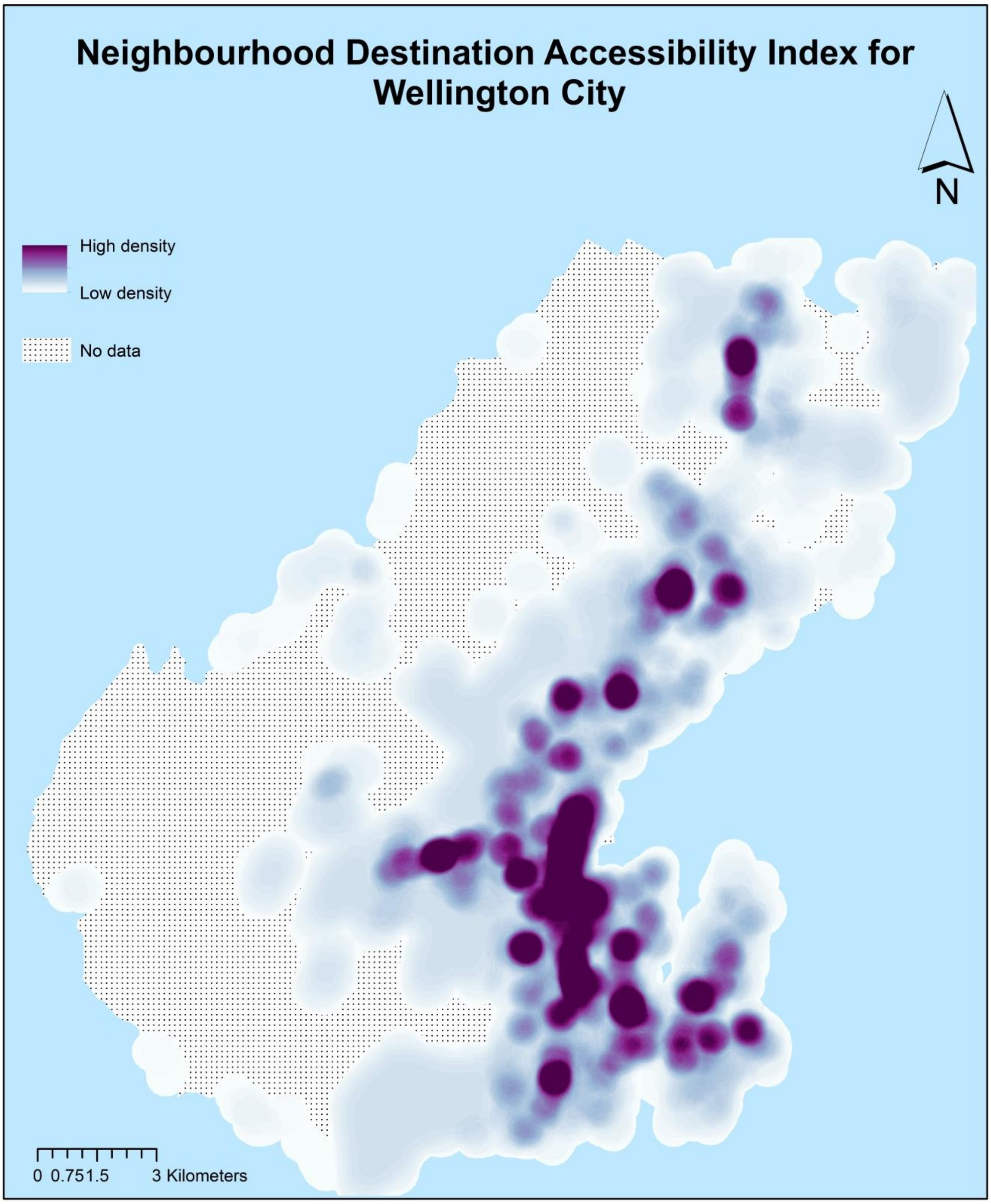


Figure 23. Kernel density map of Neighbourhood Destination Accessibility Index for Wellington City.

Table 4 provides an overview of the data sources and methods used to create each of the individual measures included in the BWIs, EWIs, BIs and NDAIs. The next section describes the steps taken to combine the individual measures into indices of walkability, bikeability and neighbourhood destination accessibility.

Table 4. Overview of the data sources and specific methods used to calculate each of the built environment measures using kernel density estimation, for Wellington City.

Measure	Database	Data source	Year	GIS methods
Land use mix	Zone areas	Wellington City Council	2014	A 100m grid was converted to points, 500m buffers were created around each point. Land zone data was intersected with the buffers. The percentage of six types of land uses, commercial, retail/industrial, open space, institutional, other, residential was calculated. An entropy index was calculated based on the presence or absence of six land use types. Values close to 1 indicated heterogeneous land uses and values close to 0 indicated homogenous land uses. These values were then used to compute kernel density estimation (KDE), a continuous surface of land use mix at a fine resolution (10m x 10m, 500m bandwidth). The measure then was standardised to deciles and included in the walk and bike indices.
Street connectivity	Road centre line	Land Information New Zealand (LINZ)	2015	Calculated road valency measure based on 3 or more intersections and road length within 500m of each node. KDE was completed with each measure and standardised to deciles. Both measures were combined to create a measure of street connectivity. This value standardised to deciles and included in the composite walk and bike indices.
Dwelling density	New Zealand Census	Statistics New Zealand	2013	Count of dwellings was used to calculate KDE. The measure was standardised to deciles and included in the composite walk and bike indices.
Footpaths and tracks	Footpaths and NZ Track Centre-lines	Wellington City Council and LINZ	2014	Line Data from Wellington City Council and LINZ were combined in order give greater coverage of walk paths through parks and alleyways. A value was of 1, indicating presence of footpaths and tracks was used to compute KDE. The measure was standardised to deciles and included in the Enhanced Walk Indices (EWIs).
Slope	Digital Elevation Model	LINZ	2014	The average slope of 100m street line segments were calculated by subtracting slope from the start of the line from the end of the line. Slope greater or equal to 8 degrees were considered unwalkable and unbikeable (given value of 0), slope less than or equal to 8 degrees was considered walkable and bikeable (value of 1), these values were used to compute KDE. Values were standardised to deciles and inverted. This measure was then included in the EWIs and Bike Indices (BIs).

Table 4. continued.

Street lights		Wellington City Council	2014	A value of 1 was assigned to point and line data indicating the presence of the built environment feature. This value was used to calculate KDE based on a fixed bandwidth of 500m and 10m x 10m cells. Each of these measures were individually standardised to deciles and included in specific composite indices. Weights were applied to each of the NDAI components, KDE was calculated based on the value attributed to each
Bike racks		Wellington City Council	2014	
Cycle lanes		Wellington City Council	2014	

NDAI	Education facilities	Wellington City Council	2014	domain. For example, transport was given a weight of 5 and social cultural a weight of 3. KDE was calculated based on these values.
	Social and cultural destinations, food outlets, financial services, retail outlets, other retail	Internet, Zenbu.co.nz	2008-2014	
	Public transport stops	Wellington City Council and Internet, Zenbu.co.nz	2015, 2008-2014	
	Health facilities	Ministry of Health and Internet, Zenbu.co.nz	2015, 2008-2014	
	Recreation (Accessible greenspace)	LINZ	2014	Similar to land use mix, a 100m grid was converted to points, 500m buffers were created around each point. The proportion of greenspace within each buffer was calculated and assigned to the point grid. These values were used to compute KDE. Values were standardised to deciles and included in the composite NDAI.

3.8 Constructing novel indices of the built environment

Indices of walkability, bikeability and neighbourhood destination accessibility

A brief summary is offered to reiterate how each index was created. After calculating the mean kernel density values for each individual built environment measure, within Euclidean (method 2) and network buffers (method 3) at a range of spatial levels, measures were standardised into deciles using the analysis tool, *Slice*, in ArcGIS, (version 10.2). Each of the measures were grouped into deciles based on equal area, where each zone represented a similar amount of area. Previous studies such as Leslie et al., (2007) and Mavoa et al., (2009) have standardised values of the built environment because each of the components have values that differ in range. Thus, in order to compare like with like, each of the elements needed to be converted to a comparable scale, such as deciles. The (deciled) individual components were summed together, similar to the standard method, using the tool, *Cell statistics*, which calculates a per-cell sum of multiple rasters (Figure 14). Land use mix, street connectivity and dwelling density, based on the novel methods 2 and 3, were combined to form a Basic Walk Index. Three additional measures, footpaths and tracks, street lights and slope, were included in the Enhanced Walk Index, based on methods 2 and 3.

An example of each measure included in the Enhanced Walk Index is included in Table 5. Values close to 60 indicate a highly walkable area and values close to 6 indicate a low walkable area. It is important to note that, values for the slope measure were inverted, where values close to 1 reflected low walkability and values close to 10 reflected high walkability, similar to each of the other components.

Table 5. Example of each standardised measure included in the Enhanced Walk Index, values close to 60 indicating areas of high walkability.

Meshblock identifier	Land use mix[a] (deciles 1-10)	Street connectivity[a] (deciles 1-10)	Dwelling density [a] (deciles 1-10)	Street lights [a] (deciles 1-10)	Footpaths and tracks [a] (deciles 1-10)	Slope [b] (deciles 1-10)	Enhanced Walk Index score (6-60)	Walk indicator
MB10001	1	3	2	2	1	1	10	Low walkability
MB10002	4	5	3	7	2	6	27	
MB19990	9	10	7	10	8	7	51	
MB19889	10	10	8	10	9	10	57	High walkability

[a] Values close to 10 = high density of features hypothesised to influence walking and cycling behaviours, (walkable/bikeable environment), values close to 1 = low density of features (unwalkable/unbikeable environment). [b] Deciled slope values were inverted. Values close to 1= high density of slope ≥ 8 degrees (unwalkable), values close to 10 = low density of slope ≥ 8 degrees (walkable).

Similar to the walk indices (BWIs, EWIs), a number of individual components were deciled and KDE values were summed to form a composite index of bikeability. Land use mix, street connectivity, slope (inverted), street lights, bike racks and cycle lanes, were included in the Bike Index (BI), and based on methods 2 and 3. In addition, each of the neighbourhood destinations, education, transport, recreation, social and cultural, food retail, financial, and health and other retail, were measured using the novel methods 2 and 3. Values were standardised to deciles and summed to create a composite index of neighbourhood destination accessibility (NDAI). A schema of each of the components included in each index is provided (Figure 24).

The walk indices (BWIs, EWIs) and NDAIs based on method 2 and 3 are investigated for associations with time spent in active transport in Chapter 5. The BWIs based on methods 1, 2 and 3, and the EWIs, BIs and NDAIs based on methods 2 and 3 are examined in relation to active transport, physical activity and health outcomes in Chapters 6 and 7, respectively.

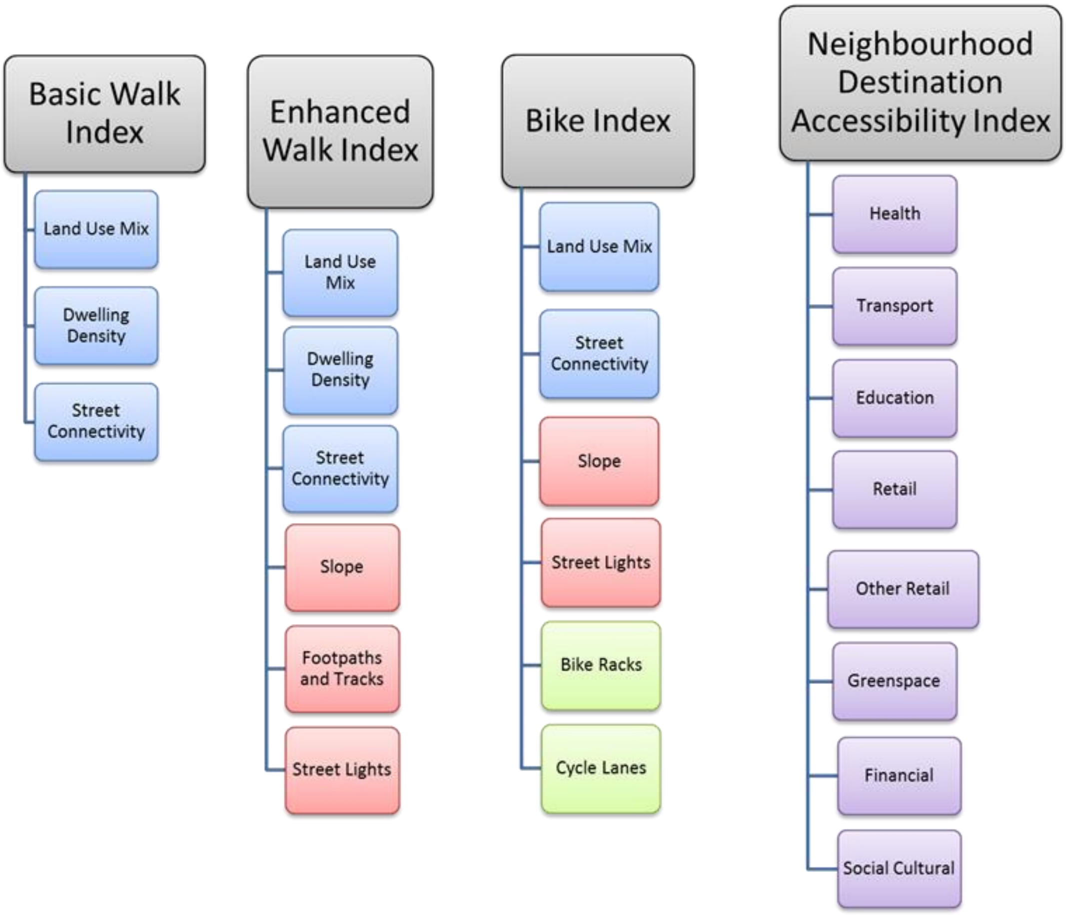


Figure 24. Schema of the components in each of the built environment indices examined in this thesis.

3.9 Conclusion

This chapter described the context, research design and study area investigated as part of this research. The standard, simple intensity methods were used to create measures of land use mix, street connectivity and dwelling density. A BWI, based on these components was created and is henceforth referred to as method 1. An alternative method of measuring the built environment, based on KDE, was described in detail for each measure included in the BWIs, EWIs, BIs and NDAIs based on methods 2 and 3. Individual and composite measures, based on methods 2 and 3, are examined with time spent in active transport in Chapter 5. Each of the indices, of the built environment, based on methods 1, 2 and 3, are investigated for associations with active transport, physical activity behaviours and health outcomes in Chapters 6 and 7, respectively. The next chapter compares each of the indices at three spatial levels, 800m, 1600m and 2400m utilising maps and histograms of the underlying data distributions.

Chapter 4: Assessing the Spatial Variations of Indices of the Built Environment

4.1 Introduction

This chapter addresses the seventh objective of this research by describing the results of each of the built environment indices described in Chapter 3, the Basic Walk Indices (BWIs) Enhanced Walk Indices (EWIs), the Bike Indices (BIs) and the Neighbourhood Destination Accessibility Indices (NDAIs). The differences between each method (standard and novel) used to create the multiple indices across multiple spatial scales are compared and contrasted. The average kernel density value for each index was calculated for multiple buffers and spatial scales using the tool zonal statistics as table. A meshblock area unit identifier was attached to the data, this enabled mapping of the indices and associated buffers at a range of scales. The maps present a new way of visualising the results of novel methods of walkability, bikeability and destination accessibility bound to the meshblock area unit. It represents a combination of deriving a fine grained analysis (KDE) of built environment features, averaging values to hypothetical neighbourhoods at a range of spatial scales but displaying the data at the meshblock area unit. Presenting the indices at a geographic level regularly used to collect information on demographic, travel and health behaviours can help health, urban and transport planners seeking to understand the influences of the built environment at a recognisable geographic scale.

A number of choropleth maps, distribution histograms and correlations are presented for a better understanding of the indices. The numerous maps presented here serve as a foundation for understanding the results in the subsequent chapters, where the indices are validated against a range of outcomes from the New Zealand Household Travel Survey, (HTS), Census and New Zealand Health Survey, (NZHS). Sections 4.2.1 and 4.2.2 describe the results of each method used to create the BWIs and EWIs (Figure 25), respectively, represented at the meshblock area unit.

Comparison between the Basic Walk Indices and Enhanced Walk Indices

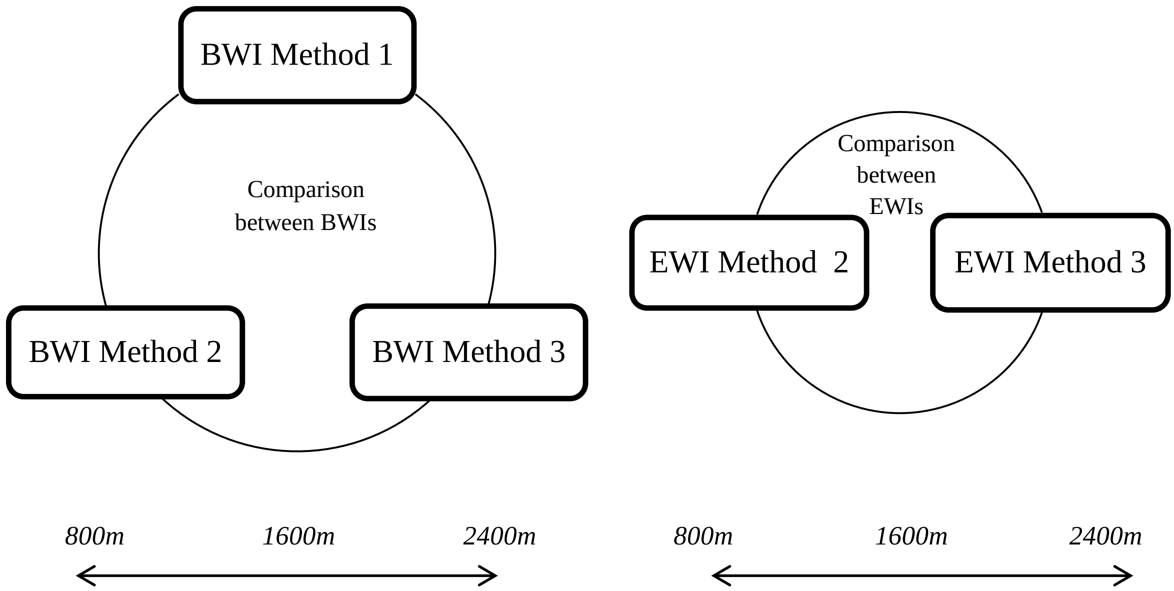


Figure 25. Schema of comparison of the Basic Walk Indices and Enhanced Walk Indices results.

Section 4.3 compares the results of each of the methods used to create the Bike Indices (BIs) and Section 4.4 describes the results of each of the NDAIs represented at the meshblock area unit (Figure 26). The chapter concludes with a description of how each of the indices will be validated in the subsequent chapters through regression analyses.

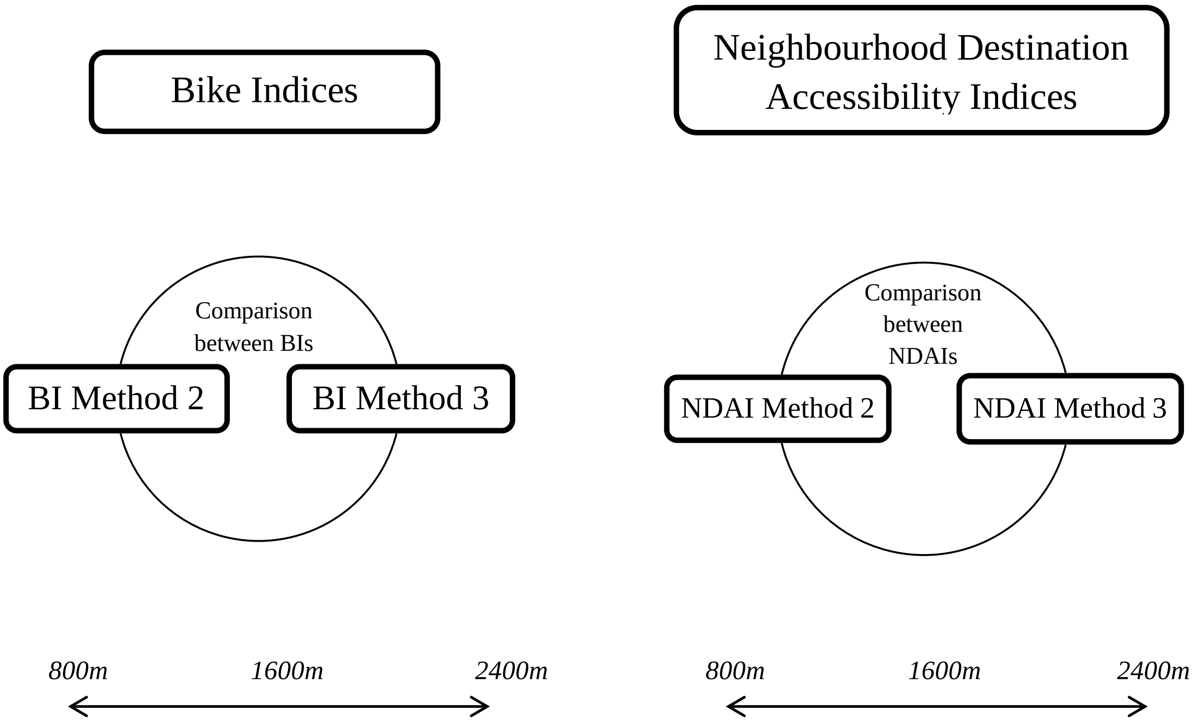


Figure 26. Schema of comparison of Bike Indices and Neighbourhood Destination Accessibility Indices results.

4.2 Walkability Indices

The following two sections present, using maps and histograms, a descriptive analysis of the multiple methods and spatial scales used to create the BWIs and EWIs. The BWIs are described first, followed by the EWIs. Table 6 provides a reminder of the methods used to create the two walkability indices, described in detail in Chapter 3, sections 3.7.1 and 3.7.2. Briefly, after generating the kernel density estimation (KDE) maps of each built environment feature at a fine spatial scale (10mx10m cells), values were standardised to deciles and *zonal statistics as table* was performed in order to calculate the mean BWI and EWI 'walkability score' for each buffer (Euclidean and network) at three spatial scales (800m, 1600m and 2400m), based on the meshblock identifier. The mean values of each index were calculated for Euclidean and network buffers, which included a meshblock identifier. This process was necessary in order to validate the indices using the Census and New Zealand Health Surveys, (Chapters 6 and 7), reported at the meshblock level.

Table 6. Methods used to create of the Basic Walk Indices and the Enhanced Walk Indices

Methods to create multiple indices	
Method 1 = BWI, standard simple intensity measure averaged to network based buffers around population weighted centroids (PWCs)	No standard method available to create the Enhanced Walk Index
Method 2 = BWI, KDE values averaged to Euclidean based buffers around PWCs	Method 2 = EWI, KDE values averaged to Euclidean based buffers around PWCs
Method 3 = BWI, KDE values averaged to network buffers around PWCs	Method 3 = EWI, KDE values averaged to network buffers around PWCs

The individual components of each index were aggregated into deciles and summed together to form an index. In order to visualise the underlying distribution of the raw data, the kernel density continuous surface maps of the BWIs and EWIs are presented in their raw form (Figure 27 and Figure 28). The darker shaded areas indicate high walkability and the lighter shaded areas indicate low walkability. Both maps indicate high walkability in central Wellington. Beyond the city centre in rural areas, both indices have low densities of walkability. No data was available to calculate walkability in the area to the west of the city due to the limited data on land use mix, street connectivity, dwellings, street lights, footpaths and tracks. This area is quite mountainous and rural. The EWI does, however, capture much more of this rural area due to the addition of slope in the index. Slope was calculated along the road network and can be seen in tubular patterns on the EWI map, (Figure 28).

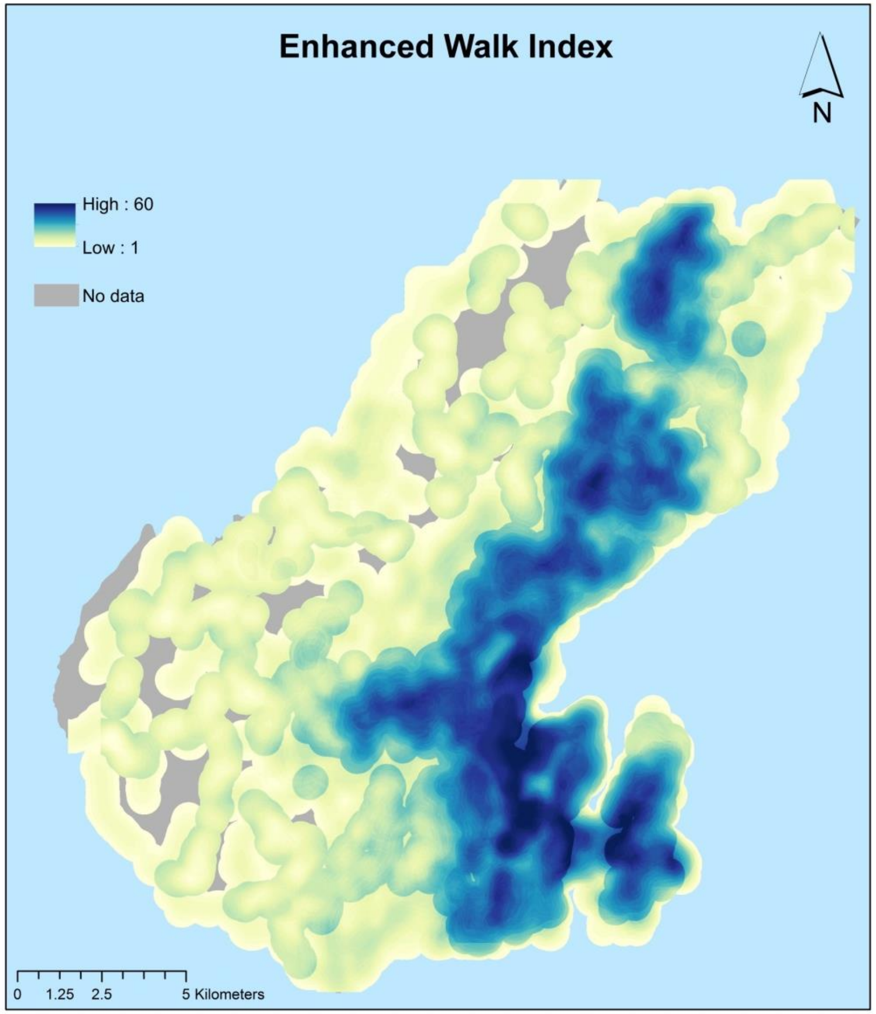


Figure 27. Kernel density map of the Basic Walk Index

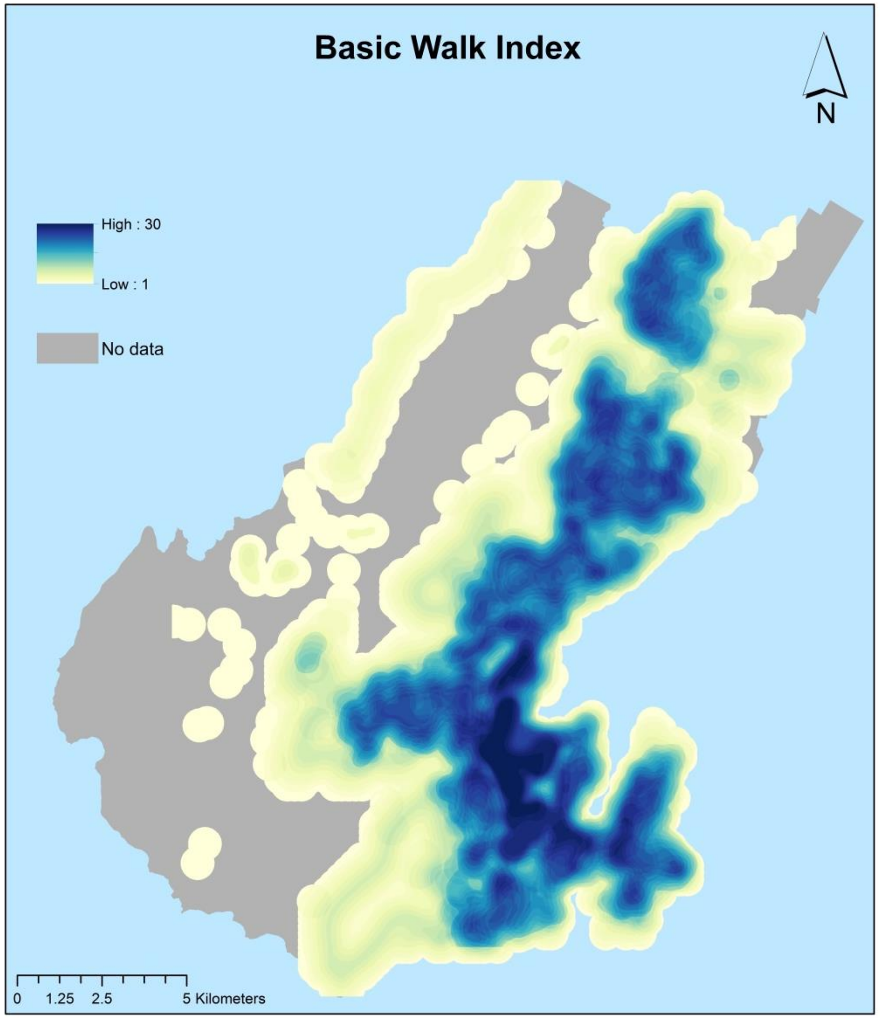


Figure 28. Kernel density map of the Enhanced Walk Index

The walkability indices (BWI, EWI) were then rescaled in order to compare methods 1, 2 and 3. This chapter explores the differences between each method based on the same scale (1-10). Furthermore, subsequent chapters investigate the BWIs and EWIs based on the same scale (1-10) with active transport and health-related data (Chapters 5, 6 and 7). The BWIs (methods 1, 2 and 3) were divided by three and the EWIs (methods 2 and 3) were divided by six (Table 7), to enable comparison between methods.

Table 7. Indices rescaled for comparison.

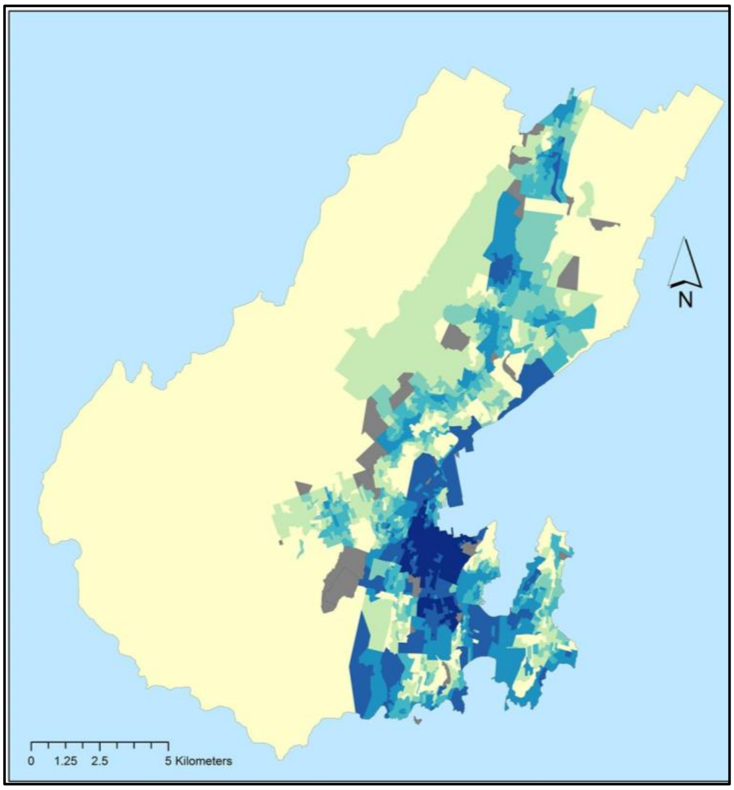
Basic Walk Indices (methods 2 and 3)	Enhanced Walk Indices (methods 2 and 3)
$BWI = \frac{\text{(Land use mix)} + \text{(dwelling density)} + \text{(street connectivity)}}{3}$	$EWI = \frac{\text{(Land use mix)} + \text{(dwelling density)} + \text{(street connectivity)} + \text{(footpaths and tracks)} + \text{(street lights)} + \text{(slope)}}{6}$

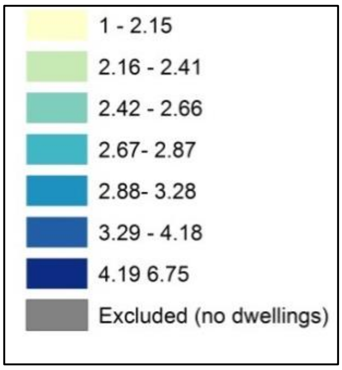
4.2.1 Basic Walk Indices

This section describes the results of the Basic Walk Indices (BWI) based on various buffers and spatial scales. The indices are mapped to meshblock polygons and quintiles representing 7 classes are used to display the variability for each BWI across multiple spatial scales and methods. It should be noted that in addition to the 35 meshblocks removed, the BWI and EWI based on method 3 (network buffers), had 7 meshblocks with no data after KDE was averaged to the meshblock level. For consistency across all maps, dark coloured areas represent high densities of walkability and light coloured areas represent low densities of walkability. Meshblocks were set to no outline in order to see the general pattern across the city.

800m Neighbourhood level

The spatial distribution of density values for the three BWIs at 800m are concentrated in Wellington City centre. The standard BWI (method 1) has a positive (right) skewed frequency distribution, whereas BWI methods 2 and 3 have negative (left) skewed distributions. The BWI based on method 2 (KDE, Euclidean buffer) and the BWI based on method 3 (network buffer) and have similar patterns of walkability with high density in the city centre. In comparison, the BWI based on method 1, has a much more mixed density of walkability surrounding the city centre. Each of the novel methods (2 and 3) have a smoother density of walkability across the meshblocks, reflecting the underlying data.





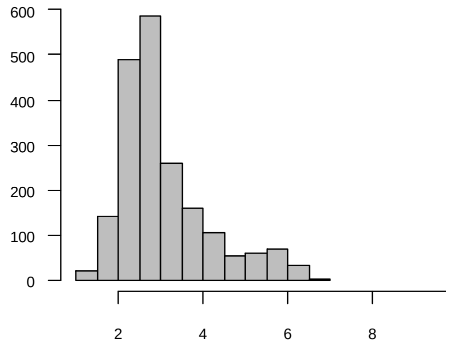


Figure 29. Basic Walk Index, standard method, network buffer around PWCs, 800m (method 1).

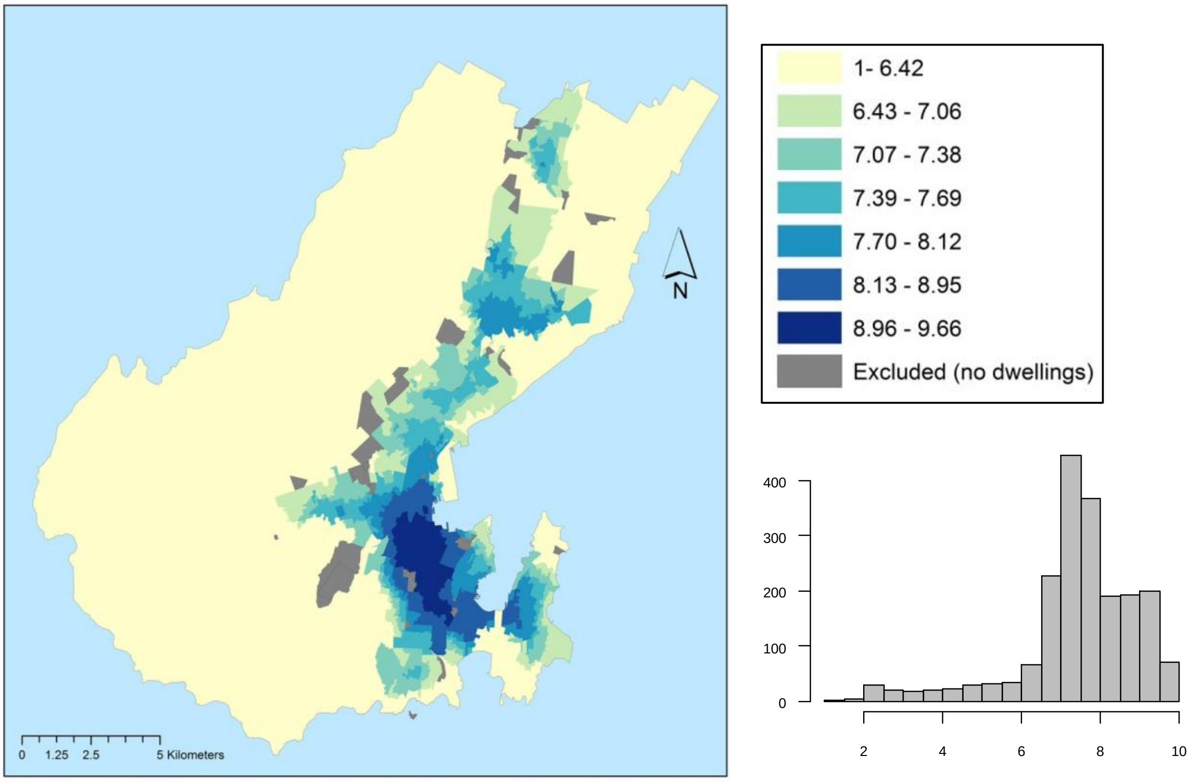
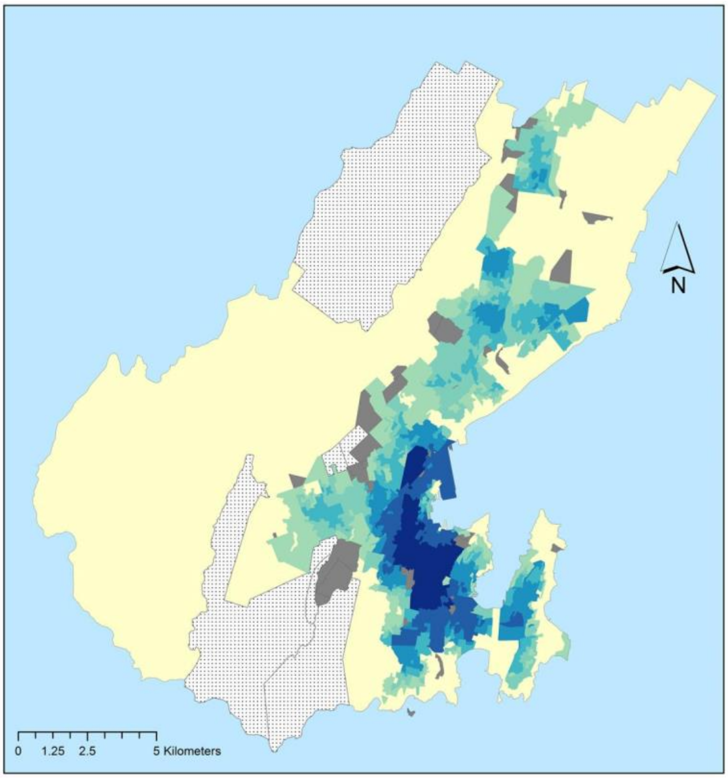


Figure 30. Basic Walk Index, novel method, Euclidean buffer around PWCs, 800m (method 2).



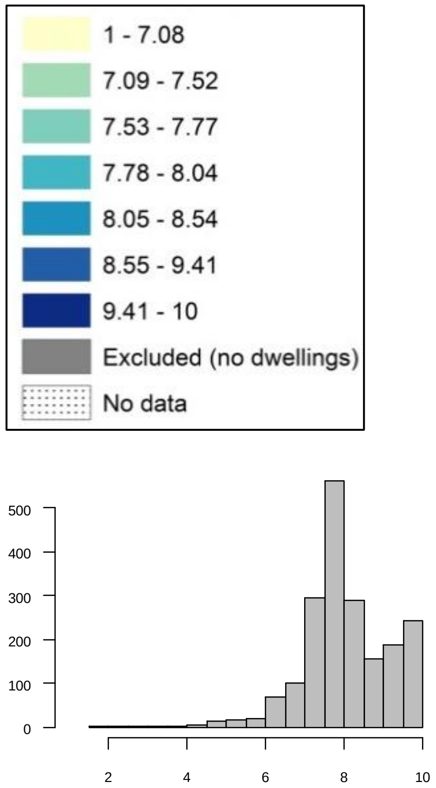
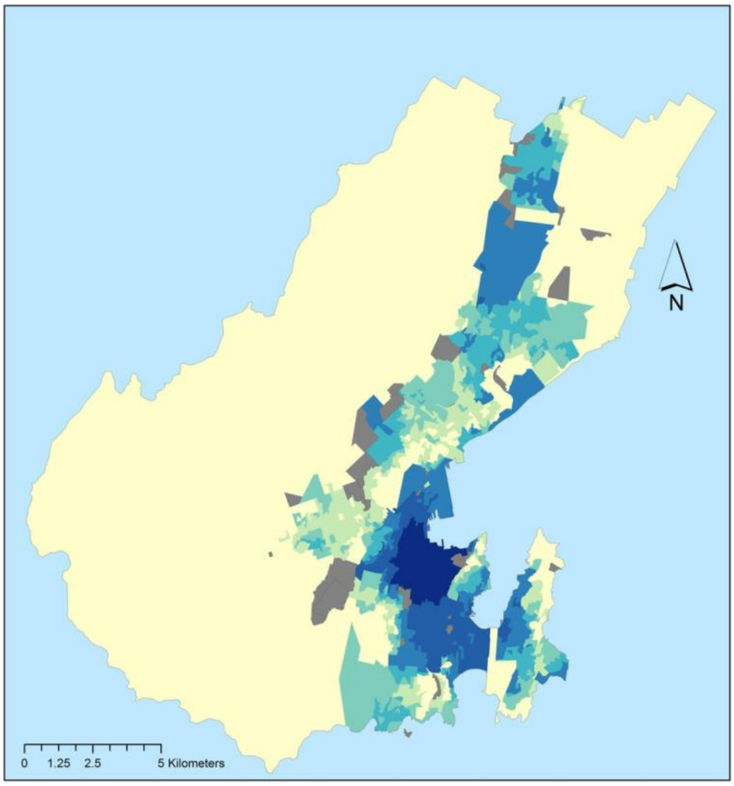


Figure 31. Basic Walk Index, novel method, network buffer around PWCs, 800m (method 3).

1600m Neighbourhood level

Results of the BWIs using the 1600m buffers are presented in the following pages in Figures 32, 33 and 34. Each index shows a similar pattern of high walkability in the city centre. Method 2 (Euclidean buffer) has a circular pattern as density of walkability features decreases from the city centre. This is expected as Euclidean buffers are circular in shape, whereas the network buffers follow the road network and have different shapes depending on distance along the road. The frequency distribution of the standard BWI (method 1) is positively skewed, while each of the kernel density BWIs (methods 2 and 3) are negatively skewed.



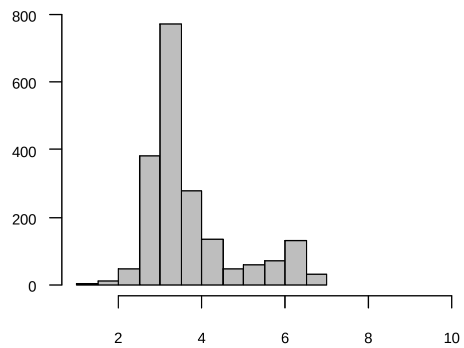


Figure 32. Basic Walk Index, standard method, network buffer around PWCs, 1600m (method 1).

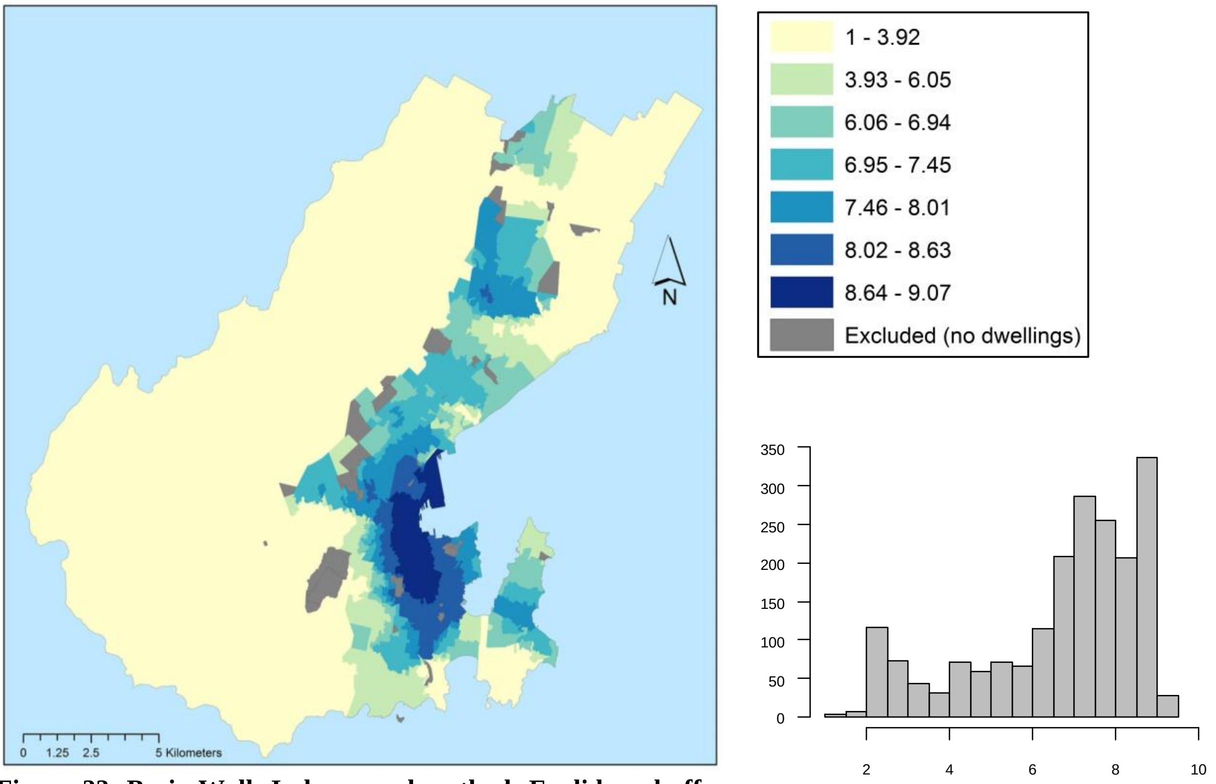


Figure 33. Basic Walk Index, novel method, Euclidean buffer around PWCs, 1600m (method 2).

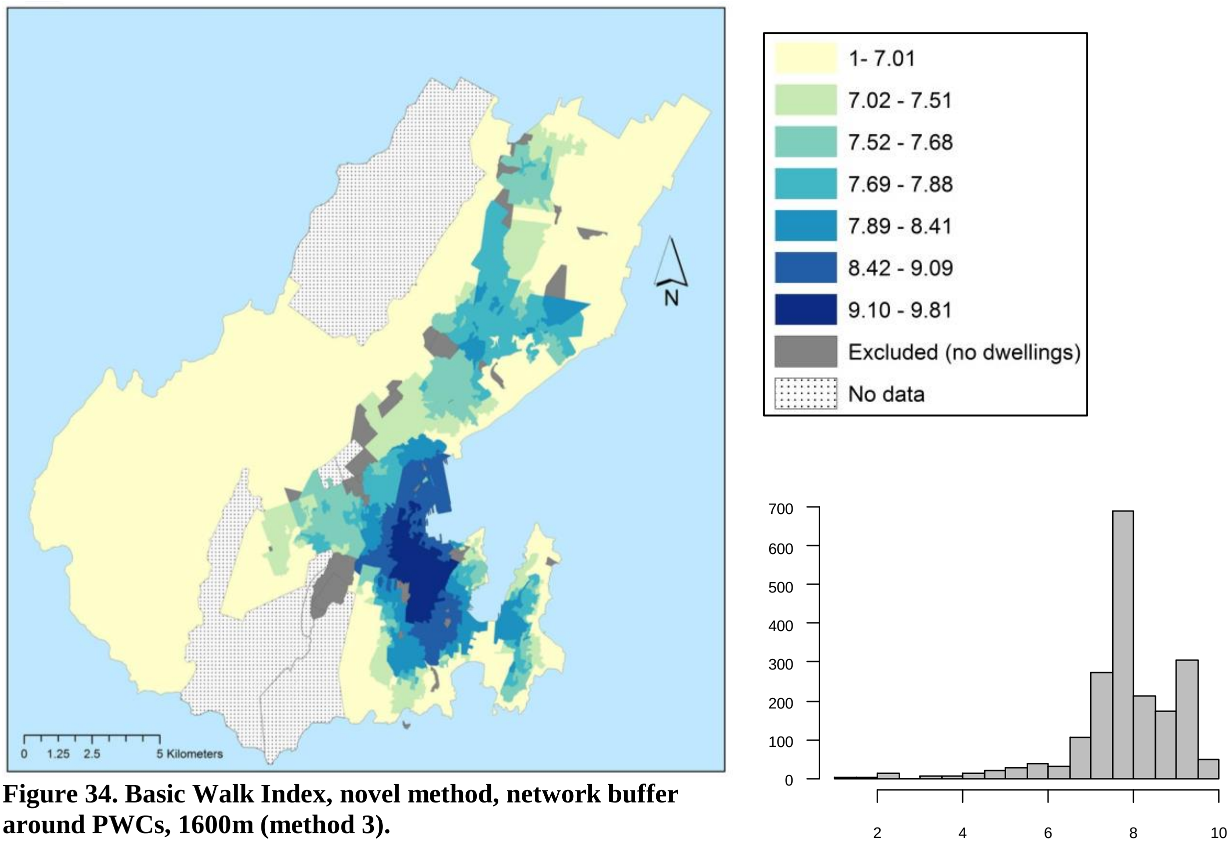
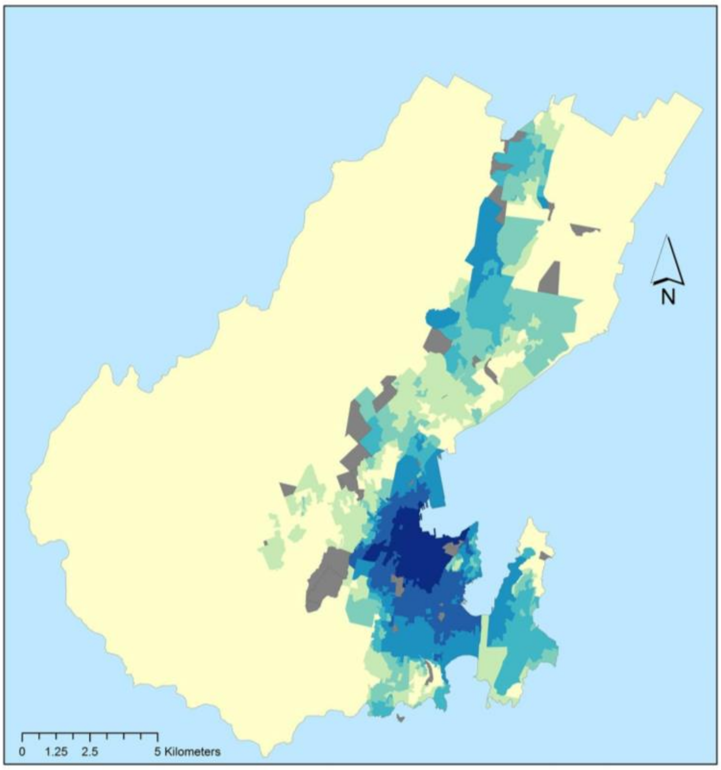


Figure 34. Basic Walk Index, novel method, network buffer around PWCs, 1600m (method 3).

2400m Neighbourhood level

At the 2400m spatial level however, the pattern changes for the BWI based on method 2, (Euclidean buffer, Figure 36) in comparison to the circular trend at the 1600m level (Figure 33). Again each index has the highest density of walkability in the city centre and decreasing values of walkability the further from the city centre. Each of the indices show similar frequency distributions to the 1600m level, with method 1 having right (positive) skewed distribution and methods 2 and 3 showing left (negative) skewed distributions.



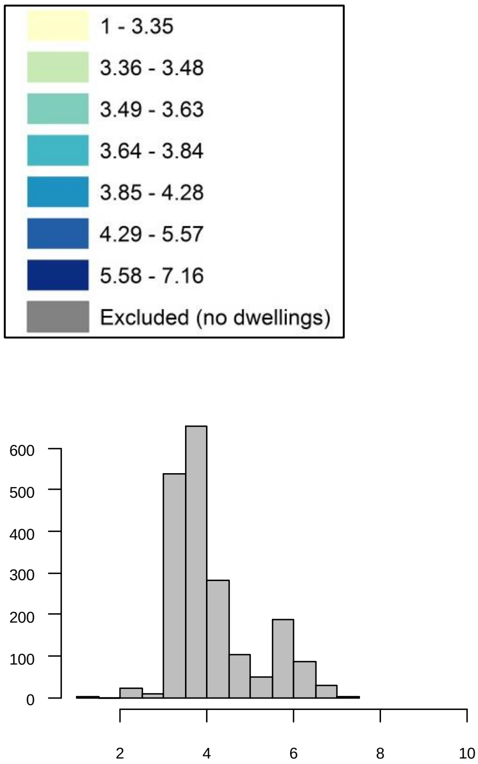


Figure 35. Basic Walk Index, standard method, network buffer around PWCs, 2400m (method 1).

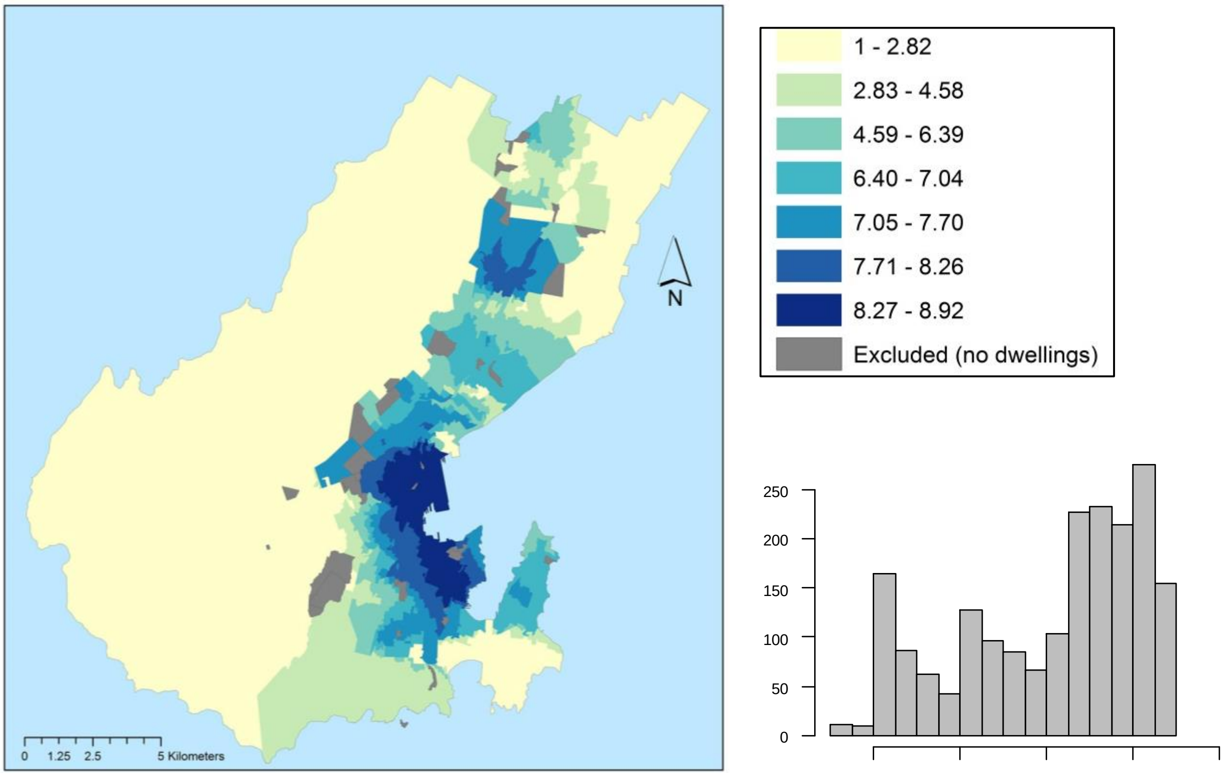


Figure 36. Basic Walk Index, novel method, Euclidean buffer around PWCs, 2400m (method 2).

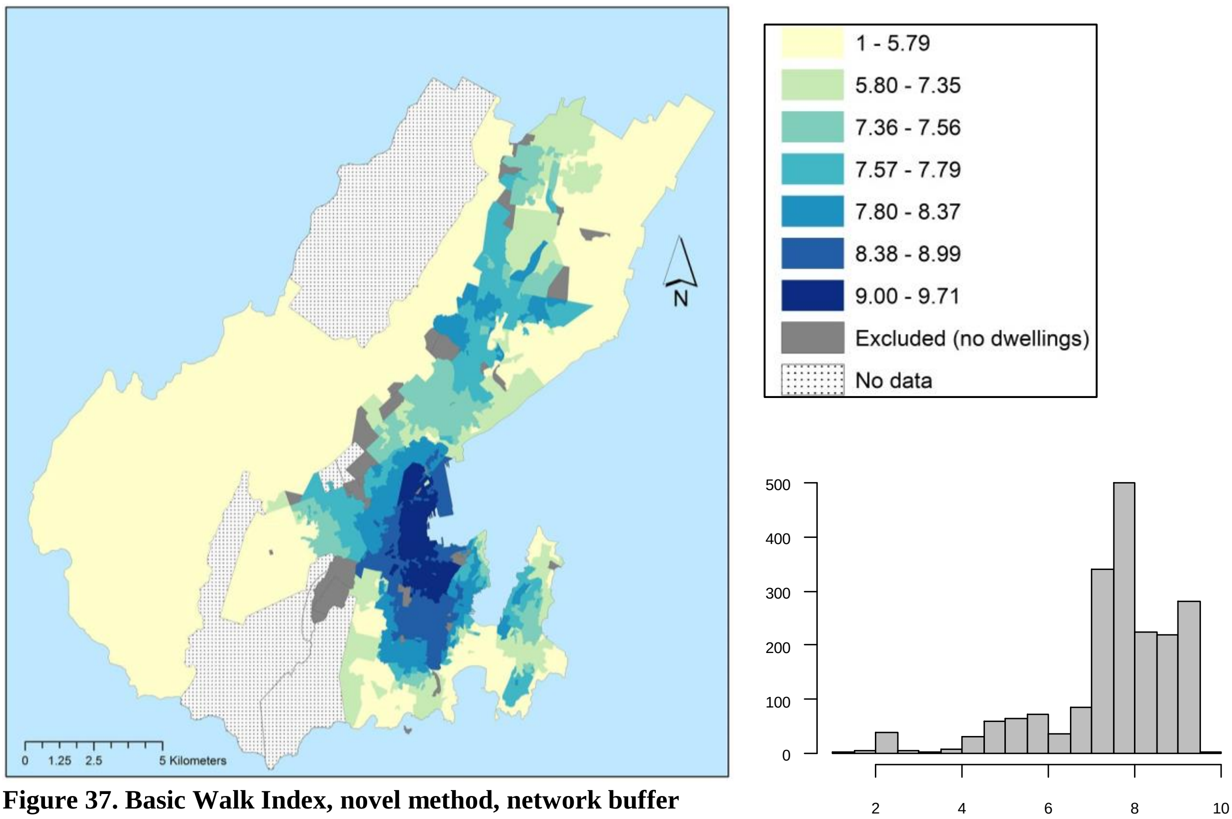


Figure 37. Basic Walk Index, novel method, network buffer around PWCs, 2400m (method 3).

4.2.2 Enhanced Walk Indices

This section reviews the results for each of the Enhanced Walk Indices (EWIs) for each spatial level, 800m, 1600m and 2400m. Similar to the BWIs, each EWI is mapped to meshblock polygons (with no outline) and uses quintiles to represent 7 classes of walkability. Dark coloured areas represent high densities of walkability.

800m Neighbourhood level

The spatial distribution of the EWI methods 2 and 3 at 800m (Figures 38 and 39) show a high density of walkability in the city centre. EWI based on method 2 (Euclidean buffer) shows a clear circular pattern around the city centre. The frequency distribution of each map at 800m is similar for BWIs based on method 2 and method 3 with left (negative) skewed distribution.

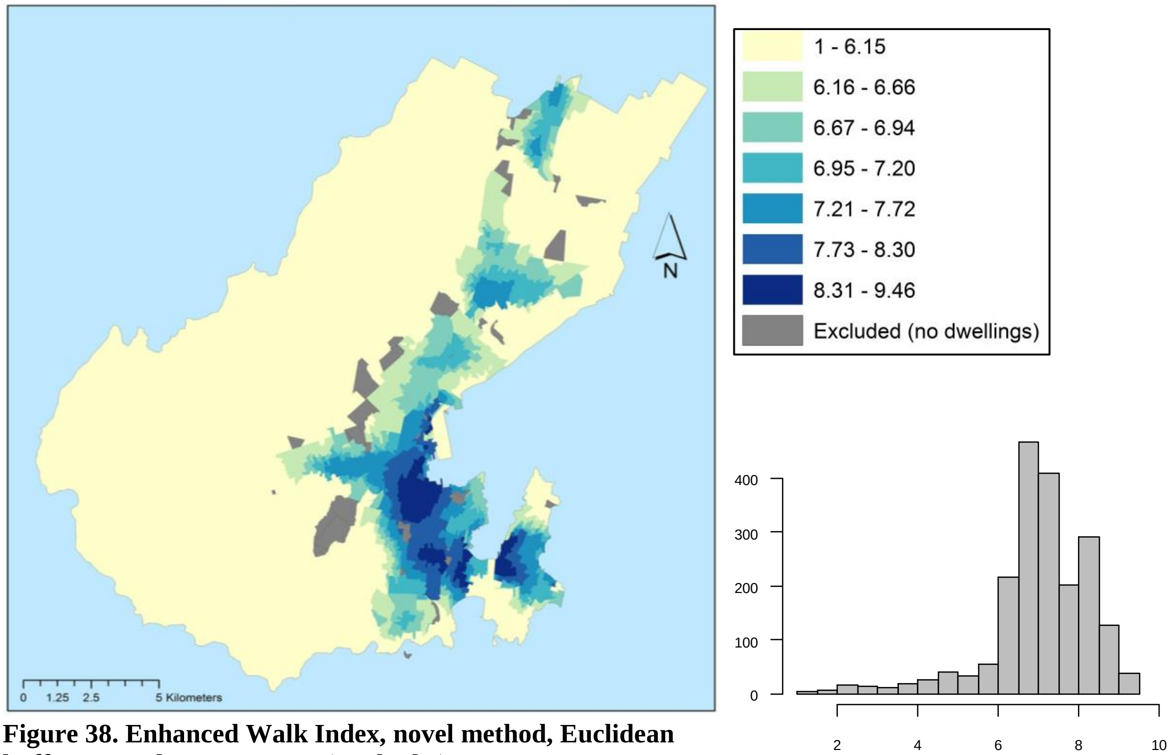
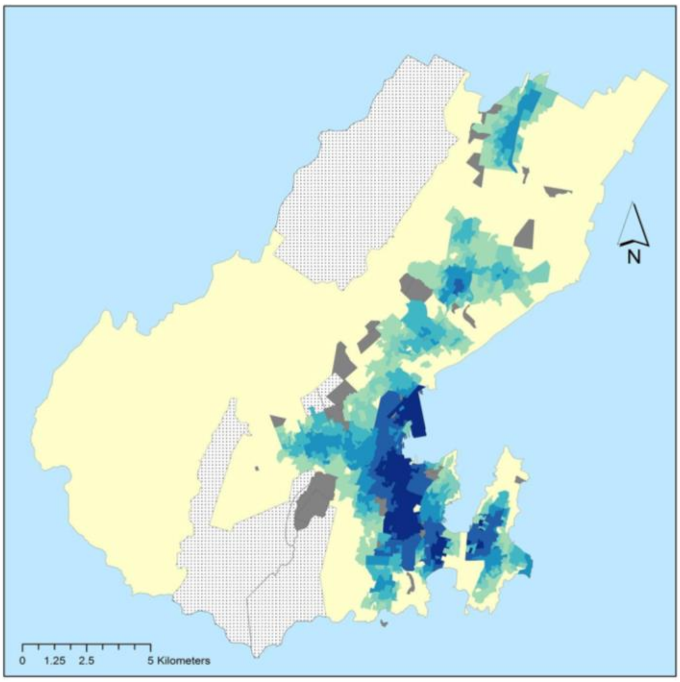
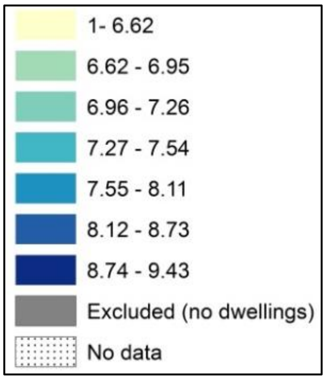


Figure 38. Enhanced Walk Index, novel method, Euclidean buffer around PWCs, 800m (method 2).

1600m Neighbourhood level

Each of the EWIs at 1600m (Figures 40 and 41) show high density of walkability around the city centre and decreasing levels of walkability in the rural areas to the left of the maps. Circular patterns are evident for method 2 (Euclidean buffer). Method 3, (network





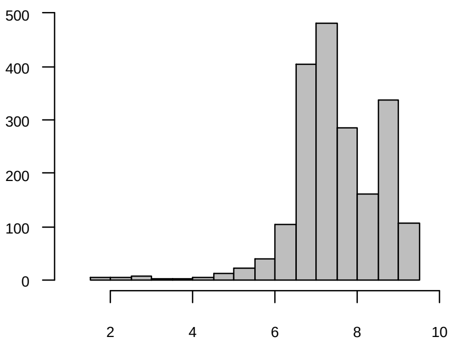


Figure 39. Enhanced Walk Index, novel method, network buffer around PWCs, 800m (method 3).

buffer) shows a contrasting mix of density around the fringes of the city centre. The frequency distribution of values for methods 2 and 3 are close to normality, only slightly negatively skewed.

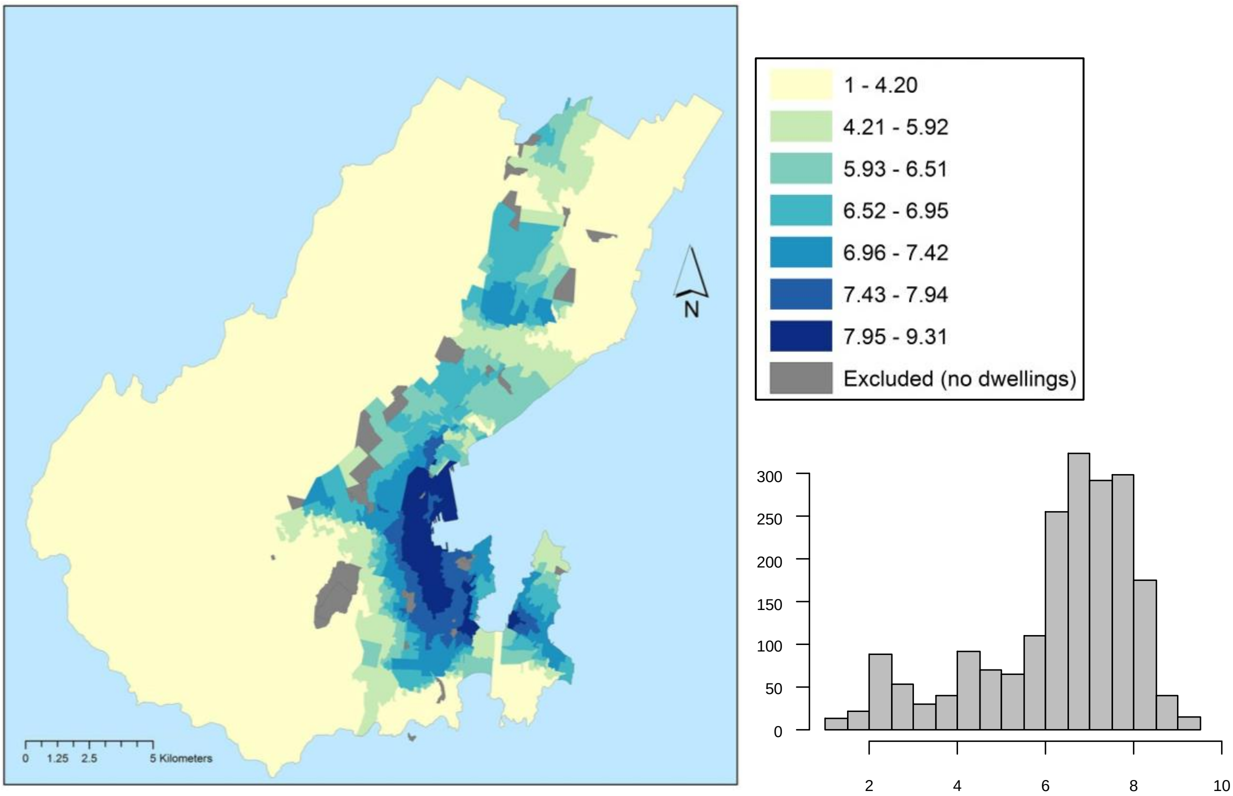


Figure 40. Enhanced Walk Index, novel method, Euclidean buffer around PWCs, 1600m (method 2).

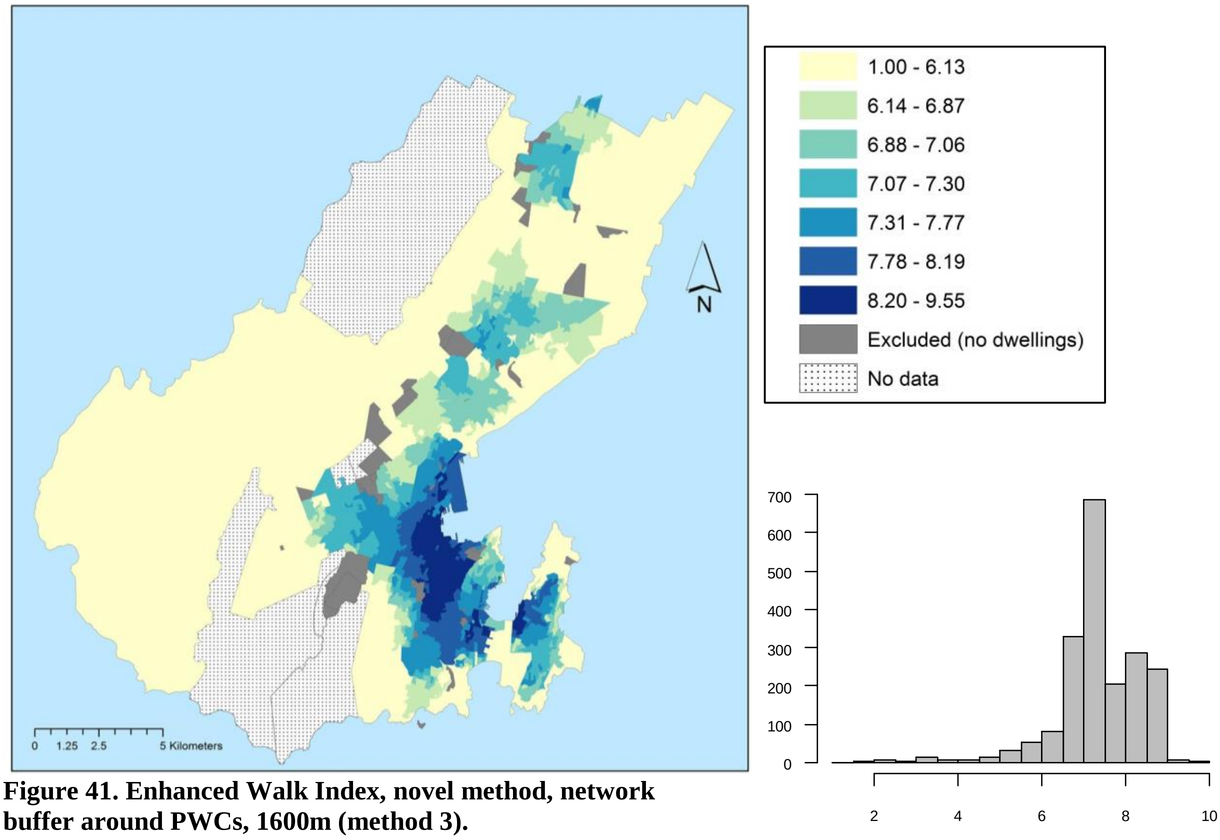


Figure 41. Enhanced Walk Index, novel method, network buffer around PWCs, 1600m (method 3).

2400m Neighbourhood level

The visual pattern in each of the EWI maps at the 2400m (Figures 42 and 43) take on a different shape to the1600m. Again, as expected, both indices have the highest density of walkability scores in the city centre. The frequency distributions are very similar to distributions reported at 1600m, methods 2 and 3 are marginally negatively skewed.

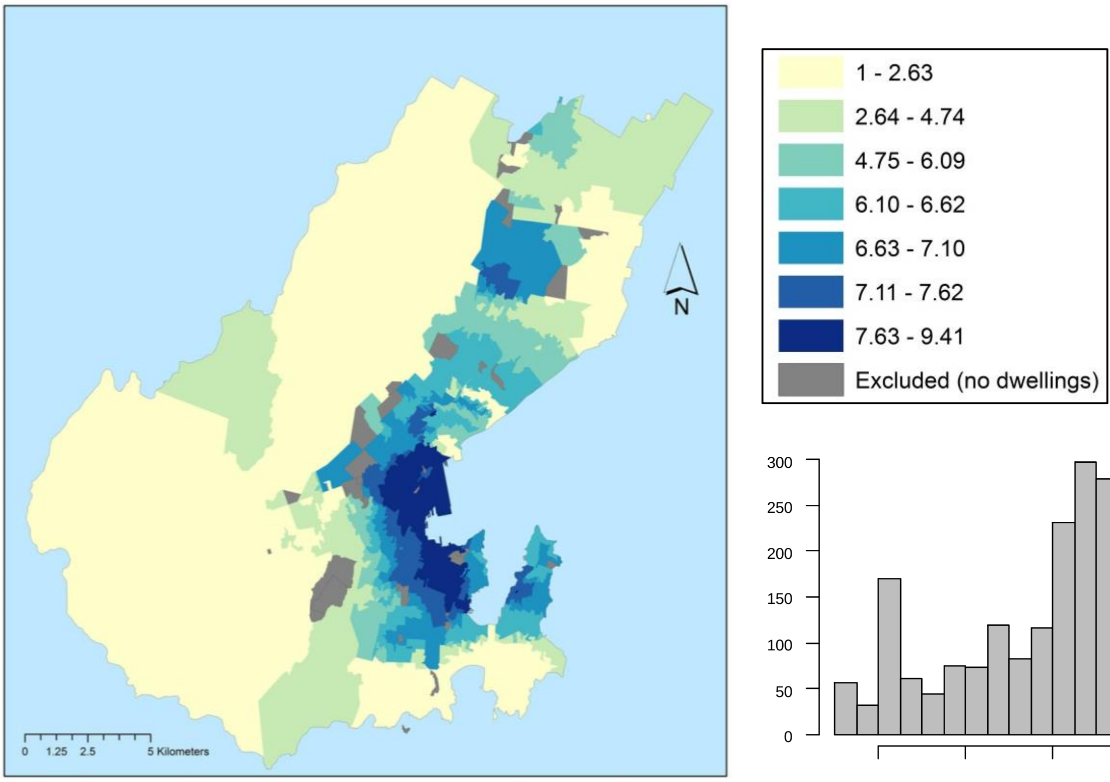


Figure 42. Enhanced Walk Index, novel method, Euclidean buffer around PWCs, 2400m (method 2).

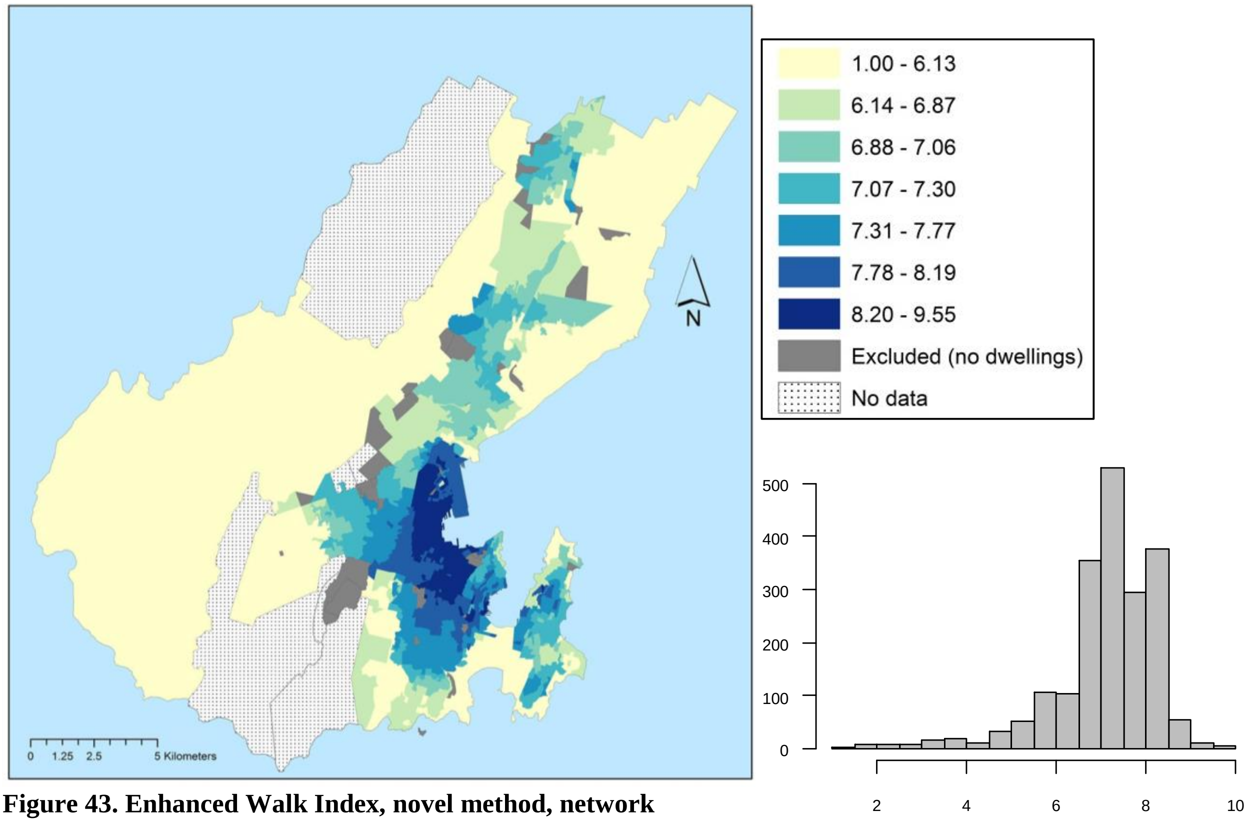


Figure 43. Enhanced Walk Index, novel method, network buffer around PWCs, 2400m (method 3).

4.2.3 Comparing the Indices

Summary statistics of each of the BWI and EWI methods at 800m, 1600m and 2400m are presented in Table 8. Across each of the spatial levels, the values for the standard BWI based on method 1, are lower for the maximum, mean and median values in comparison to each of the kernel density methods (2 and 3). A contrasting pattern emerges for the BWIs and EWIs based on methods 2 and 3, where the mean and median decrease steadily as the spatial scale increases.

Table 8. Descriptive table of the Basic Walk Indices and Enhanced Walk Indices using various buffers and spatial levels.

800m	**Mean**	**Median**	**Std.**
BWI (Method 1)	3.05	2.76	1.07
BWI (Method 2)	7.39	7.53	1.60
BWI (Method 3)	7.97	7.83	1.27
EWI (Method 2)	7.00	7.06	1.35
EWI (Method 3)	7.45	7.42	1.10
1600m			
BWI (Method 1)	3.68	3.32	1.13
BWI (Method 2)	6.62	7.17	2.05
BWI (Method 3)	7.78	7.80	1.31
EWI (Method 2)	6.28	6.68	1.78
EWI (Method 3)	7.33	7.27	1.05
2400m	**Mean**	**Median**	**Std.**
BWI (Method 1)	4.07	3.72	1.01
BWI (Method 2)	6.03	6.78	2.18
BWI (Method 3)	7.47	7.70	1.55
EWI (Method 2)	5.70	6.40	2.00
EWI (Method 3)	7.11	7.17	1.14

Pearson’s correlations between each of the BWIs and EWIs based on methods 1, 2 and 3, across the three spatial levels are presented in Table 9. The novel BWIs (methods 2 and 3) have a strong positive linear relationship with the novel EWIs (methods 2 and 3), indicating they are similar measures. When comparing the standard BWI (method 1) with the novel BWIs and EWIs, the linear relationship is not as strong. To summarise, the novel BWI is more similar to the novel EWI than to the standard BWI, indicating that the novel method is driving the difference. In addition, the additional parameters, slope, street lights and footpaths and tracks, did not impact the results greatly. While the Pearson’s correlations shows there is a linear relationship, it does not indicate whether the novel approach has a better model fit than the standard approach. In the subsequent chapters the standard and novel methods are tested using various regression analyses to determine which method of measuring the built environment shows stronger associations with active transport, physical activity and health outcomes.

Table 9. Pearson's correlations comparing the various Basic and Enhanced Walk Indices for 800m, 1600m and 2400m spatial scales, (α= 5%, p<0.001).

Neighbourhood definition	BWI (Method 1)	BWI (Method 2)	BWI (Method 3)	EWI (Method 2)	EWI (Method 3)
800m					
BWI (Method 1)	1.00	0.59	0.66	0.58	0.68
BWI (Method 2)		1.00	0.76	0.95	0.76
BWI (Method 3)			1.00	0.74	0.93
EWI (Method 2)				1.00	0.79
EWI (Method 3)					1.00
1600m					
BWI (Method 1)	1.00	0.61	0.67	0.57	0.70
BWI (Method 2)		1.00	0.62	0.94	0.63
BWI (Method 3)			1.00	0.62	0.94
EWI (Method 2)				1.00	0.64
EWI (Method 3)					1.00
2400m					
BWI (Method 1)	1.00	0.55	0.61	0.52	0.65
BWI (Method 2)		1.00	0.64	0.93	0.62
BWI (Method 3)			1.00	0.66	0.96
EWI (Method 2)				1.00	0.64
EWI (Method 3)					1.00

Summary

Clustered patterns of walkability scores in each of the maps reflects the high walkability density in the city centre in both the BWIs and EWIs. This is expected, as the components that make up each of the indices are more concentrated in the city centre, i.e. street connectivity, dwelling density, land use mix, street lights, footpaths and slope. Similarly, high density around the city centre in each of the KDE measures (methods 2 and 3) is expected since the methods are based on the same underlying data. However, patterns emerge at 1600m and 2400m and differences between the types of buffer, Euclidean and network, can be seen. It is interesting to note however, that the standard BWI based on method 1 also has similar walkability patterns to the novel methods (2 and 3), for most spatial scales, potentially indicating that the novel methods are a valid alternative to the standard BWI (method 1). This hypothesis will be tested in Chapter 6 and 7, when validating the indices with Census and New Zealand Health Survey (NZHS) data. Correlation values for each BWI and EWI and their respective methods were very high, which is expected since the EWIs includes the same data as the BWIs, with three additional components. Each of the methods used to create the BWIs and EWIs, their visual differences and similarities, offer insights into the subtle differences between buffers and spatial scales.

4.3 Bikeability Indices

The following section describes the results of the Bike Indices for methods 2 and 3. Choropleth maps, frequency distribution histograms, summary statistics and Pearson's correlations are presented. Table 10 presents the six components of the Bike Index. Each of the individual components were standardised to deciles and summed into an index of bikeability ranging from 6-60.

Table 10. Bike Index components.

BI = (Land use mix) + (Street connectivity) + (Street lights) + (Slope) + (Bike racks) + (Cycle lanes)

Similar to the walk indices, a map of the kernel density continuous surface of bikeability for Wellington City is presented, to visualise the underlying distribution of raw data (Figure 44). Areas where there was no data on land use mix, street connectivity, street lights, cycle lanes and bike racks are represented in grey. Darker areas represent high bikeability and lighter coloured areas represent low bikeability. Similar to the BWI and the EWI maps, (Figures 27 and 28), high bikeability is concentrated around the city centre and decreases as distance increases further from the city. Due to the addition of slope in the Bike Index, areas outside the city centre have low bikeability. It is acknowledged that mountainous areas are attractive to certain types of cyclists, however this research is interested in cycling for active transport and physical activity for the general population, not specific sub groups.

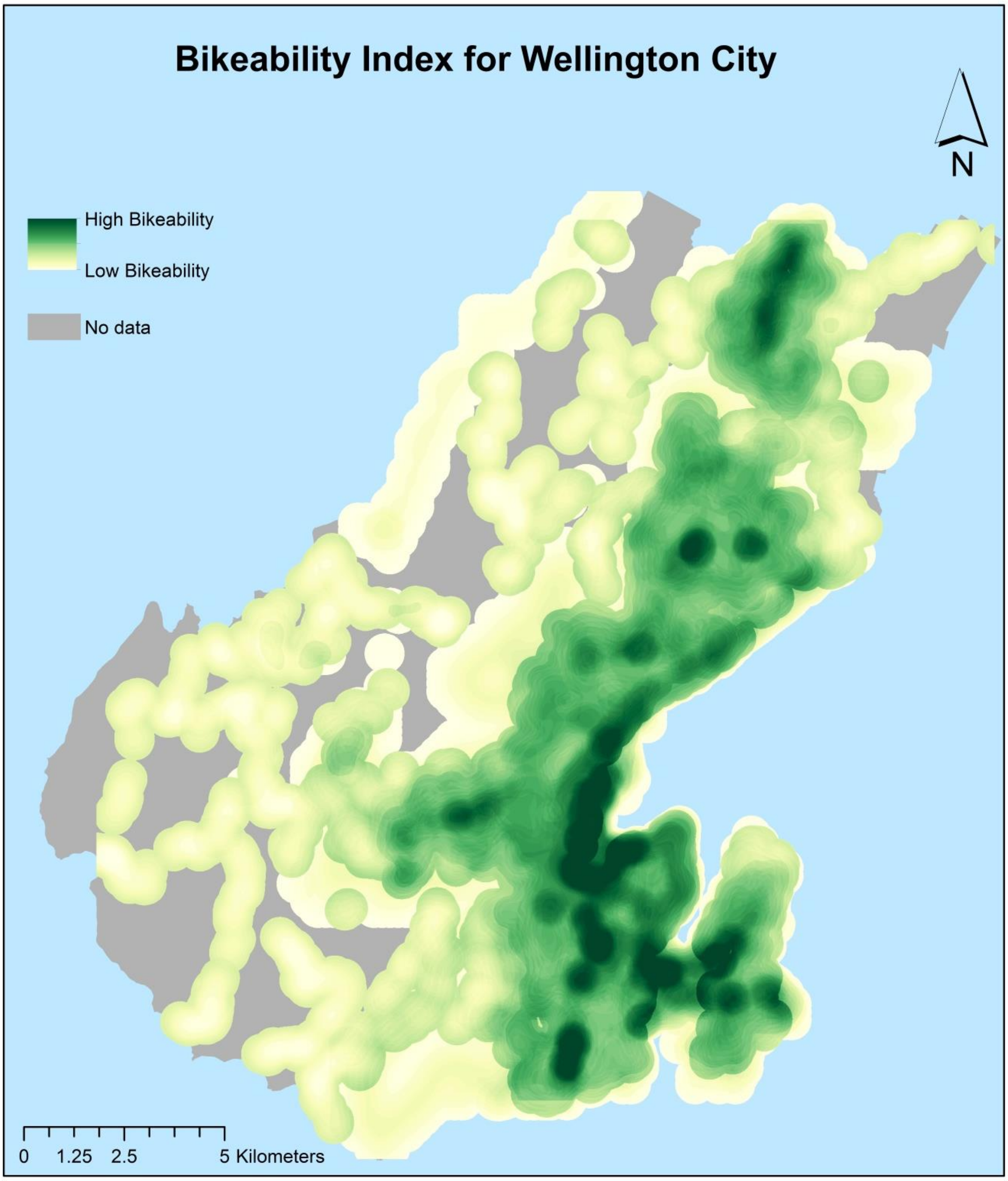
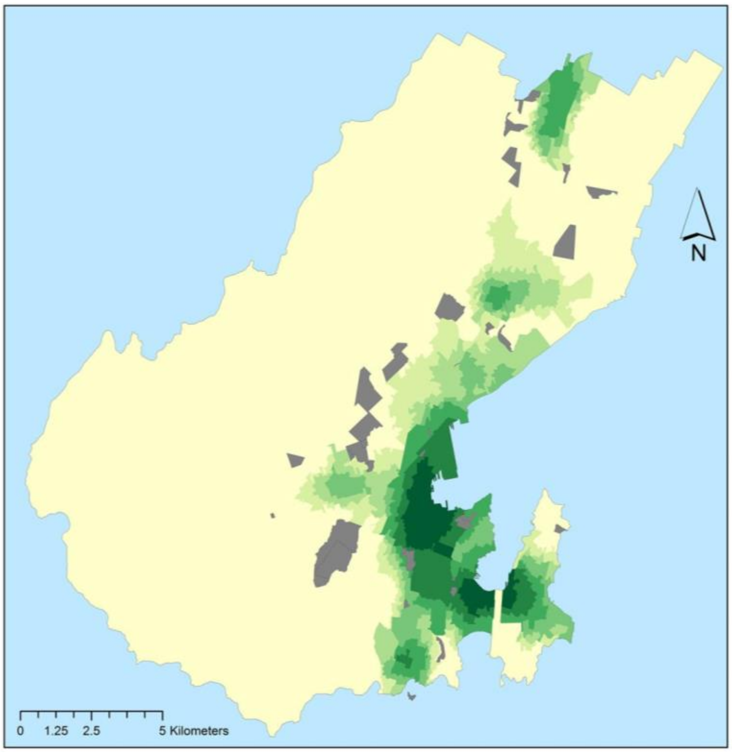


Figure 44. Kernel density map of the Bikeability Index for Wellington City.

The Bike Index (BI) was then averaged to Euclidean (method 2) and network (method 3) based buffers at 800m, 1600m and 2400m around meshblock population weighted centroids. The next three sections give a brief description of the visual representation of the BIs, (methods 2 and 3) at each spatial level. Values close to 60 represent areas with high bikeability scores and areas with low values, close to 6, represent low bikeability scores.

800m Neighbourhood level

Both maps (Figures 45 and 46) have similar bikeability scores in Wellington City. Visually, high bikeability is concentrated in the city centre with decreasing bikeability density the further from the centre. The BI based on method 3 has a higher concentration of values in the highest quintile in comparison to the BI based on method 2. In addition, both BIs (methods 2 and 3) are normally distributed.



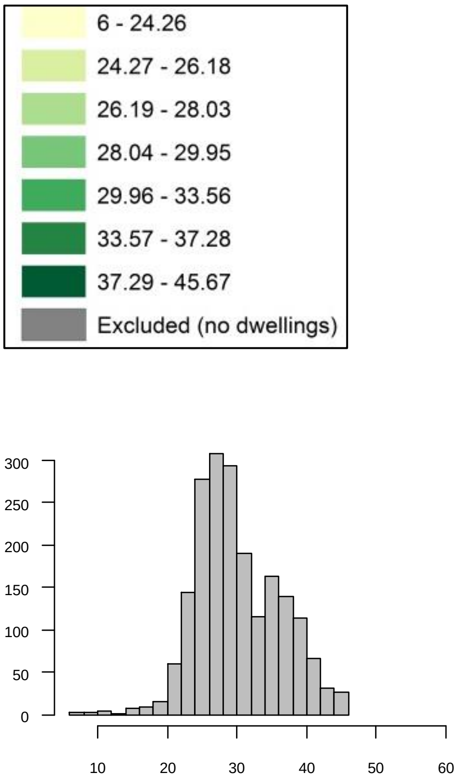
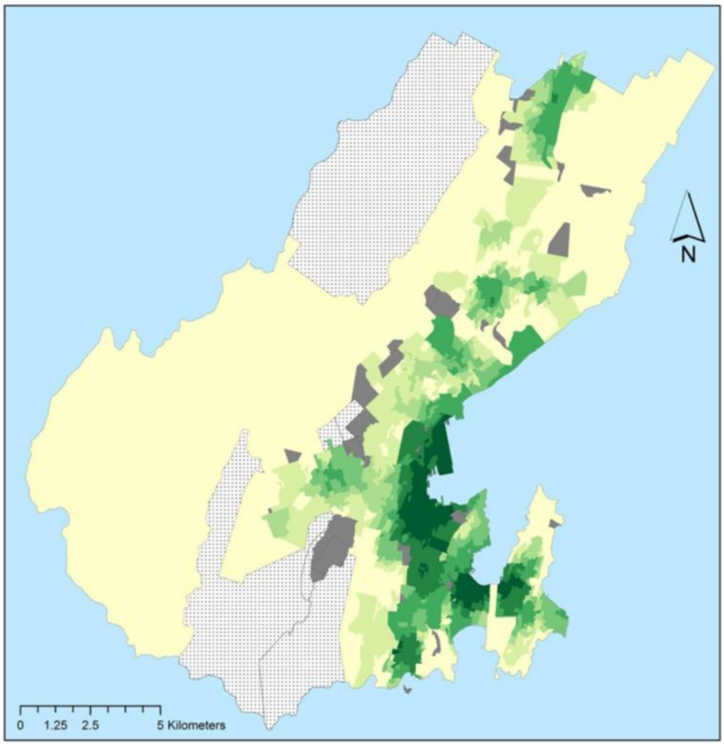


Figure 45. Bike Index, novel method, Euclidean buffer around PWCs, 800m (method 2).



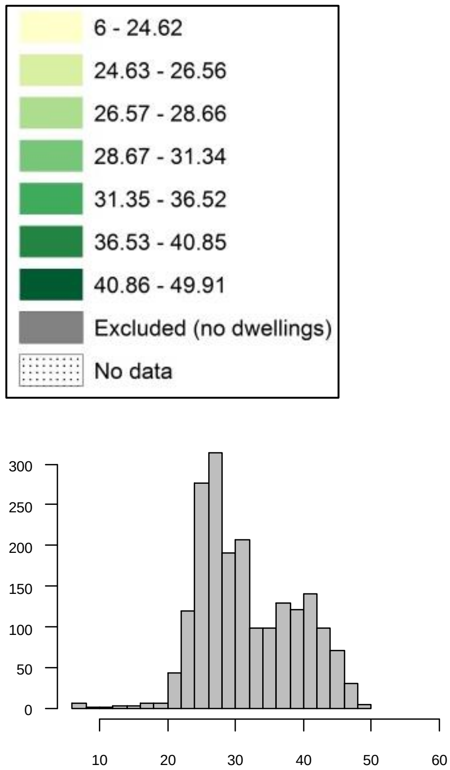


Figure 46. Bike Index, novel method, network buffer around PWCs, 800m (method 3).

1600m Neighbourhood level

Patterns emerge at the 1600m spatial scale, with the BI based on method 2, (Figure 47), displaying a circular form of bikeability density in the city centre. This is expected as method 2 is based on Euclidean buffers. In contrast, the BI based on method 3, (Figure 48), has a more disjointed pattern of bikeability density, reflecting the network based buffers. Similar to the BIs at 800m, the BI based on method 3 has higher values of bikeability in the highest quintile in comparison to the BI based on method 2. In addition, the underlying frequency distribution of both BIs is normally distributed.

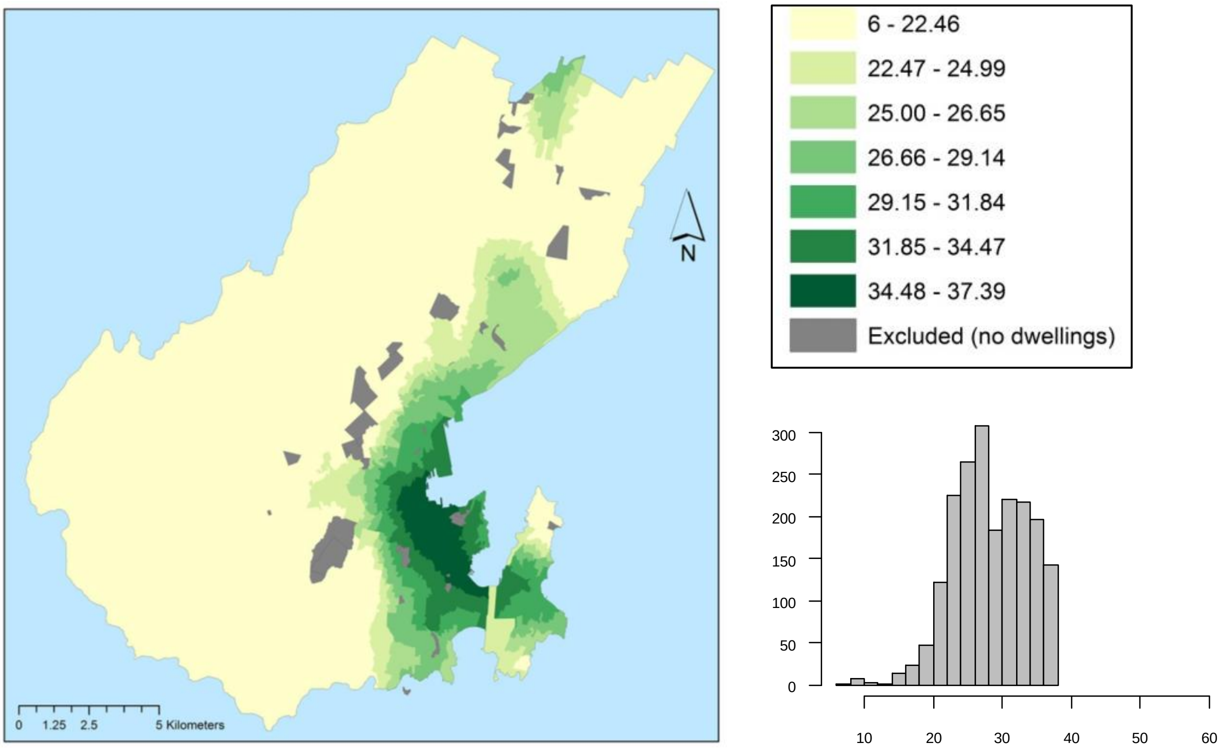


Figure 47. Bike Index, novel method, Euclidean buffer around PWCs, 1600m (method 2).

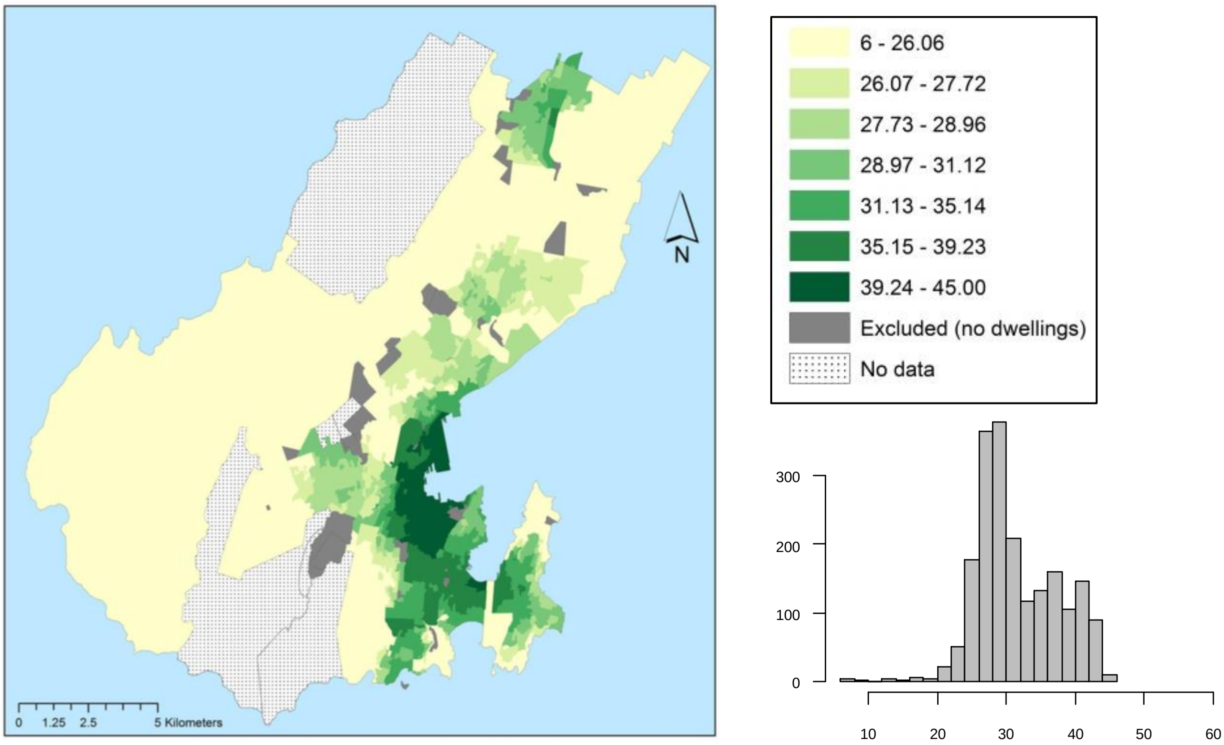
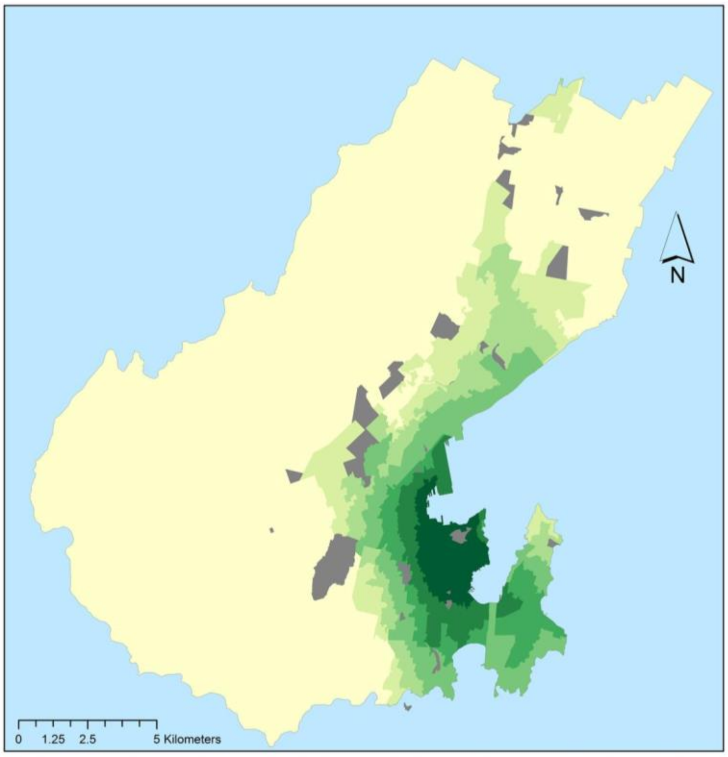


Figure 48. Bike Index, novel method, network buffer around PWCs, 1600m (method 3).

2400m Neighbourhood level

Similar to the 1600m spatial level, distinct circular patterns of bikeability density from the city centre are evident in the BI based on method 2 (Figure 49). The BI based on method 3, (Figure 50), also displays a circular pattern in the highest quintile in the city centre. In addition, as with the 800m and 1600m scales, both BIs have frequency distributions close to normality.



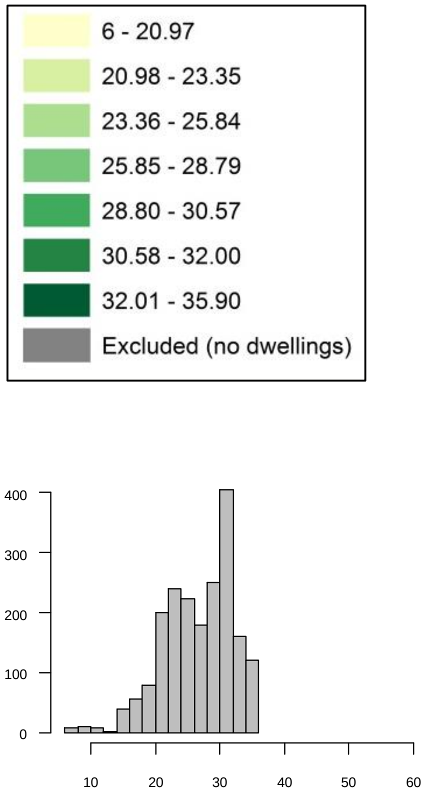


Figure 49. Bike Index, novel method, Euclidean buffer around PWCs, 2400m (method 2).

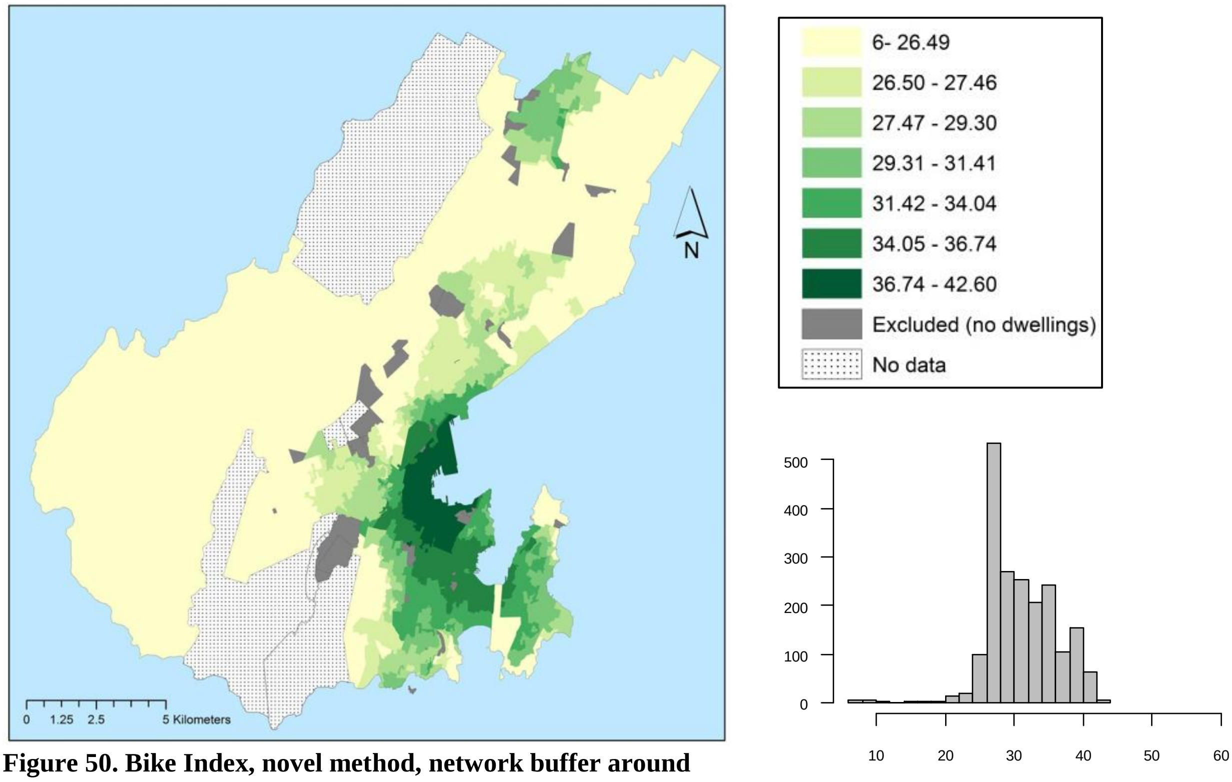


Figure 50. Bike Index, novel method, network buffer around PWCs, 2400m (method 3).

Descriptive statistics of the BIs based on methods 2 and 3 at 800m, 1600m and 2400m are shown in Table 11. Across each of the spatial levels the values for the BI based on method 3 are higher than the BI based on method 2. In both BIs, the mean values decrease as the spatial scale increases.

Table 11. Summary statistics of the Bike Indices using various methods and spatial levels.

	Min	Max	Mean	Median	Std.
800m					
BI (Method 2)	6.00	45.68	29.92	28.86	6.40
BI (Method 3)	6.00	49.91	31.62	30.15	7.29
1600m					
BI (Method 2)	6.00	37.40	28.04	27.70	5.53
BI (Method 3)	6.00	45.01	31.44	29.80	6.03
2400m					
BI (Method 2)	6.00	35.90	26.56	27.32	5.54
BI (Method 3)	6.00	42.61	31.03	30.29	4.98

Correlations between the BIs were relatively high (0.77 at 800m, 0.85 at 1600m and 0.79 at 2400m). Methods 2 and 3 are most strongly correlated at the 1600m spatial level (Table 12).

Table 12. Pearson's correlation of Bike Indices for each method for 800m, 1600m and 2400m spatial scales, (α= 5%, p<0.001).

Neighbourhood Definition	BI (Method 2)	BI (Method 3)
800m		
BI (Method 2)	1.00	0.77
BI (Method 3)		1.00
1600m		
BI (Method 2)	1.00	0.85
BI (Method 3)		1.00
2400m		
BI (Method 2)	1.00	0.79
BI (Method 3)		1.00

Summary

This section described the visual representation of the BIs based on methods 2 and 3 at three spatial levels, 800m, 1600m and 2400m. Both methods show high concentration of bikeability scores in the city centre. Circular patterns emerge at 1600m and 2400m for method 2 based on the Euclidean buffer. Furthermore, the frequency distribution of the underlying data was normally distributed for both BIs across each spatial scale. The BIs based on method 2 and 3 are investigated for associations with active transport, physical activity and health outcomes in subsequent chapters 5, 6 and 7.

4.4 Neighbourhood Destination Accessibility Indices

The following section describes the results of the NDAIs using methods 2 and 3 for each spatial level, 800m, 1600m and 2400m. Choropleth maps, distribution histograms, summary statistics and Pearson's correlation results are presented. Similar to the walk and bike indices, described previously, each of the individual components (education, transport, recreation, social and cultural, food retail, financial, and health and other retail) were created using KDE. Values were standardised to deciles and summed together to form an index of neighbourhood destination accessibility. Figure 51 displays the raw KDE values of the NDAI for Wellington City. The city centre has a higher density of darker colours, representing areas with high density of destinations. Clusters of high density NDAI scores are dotted north and south of the city centre.

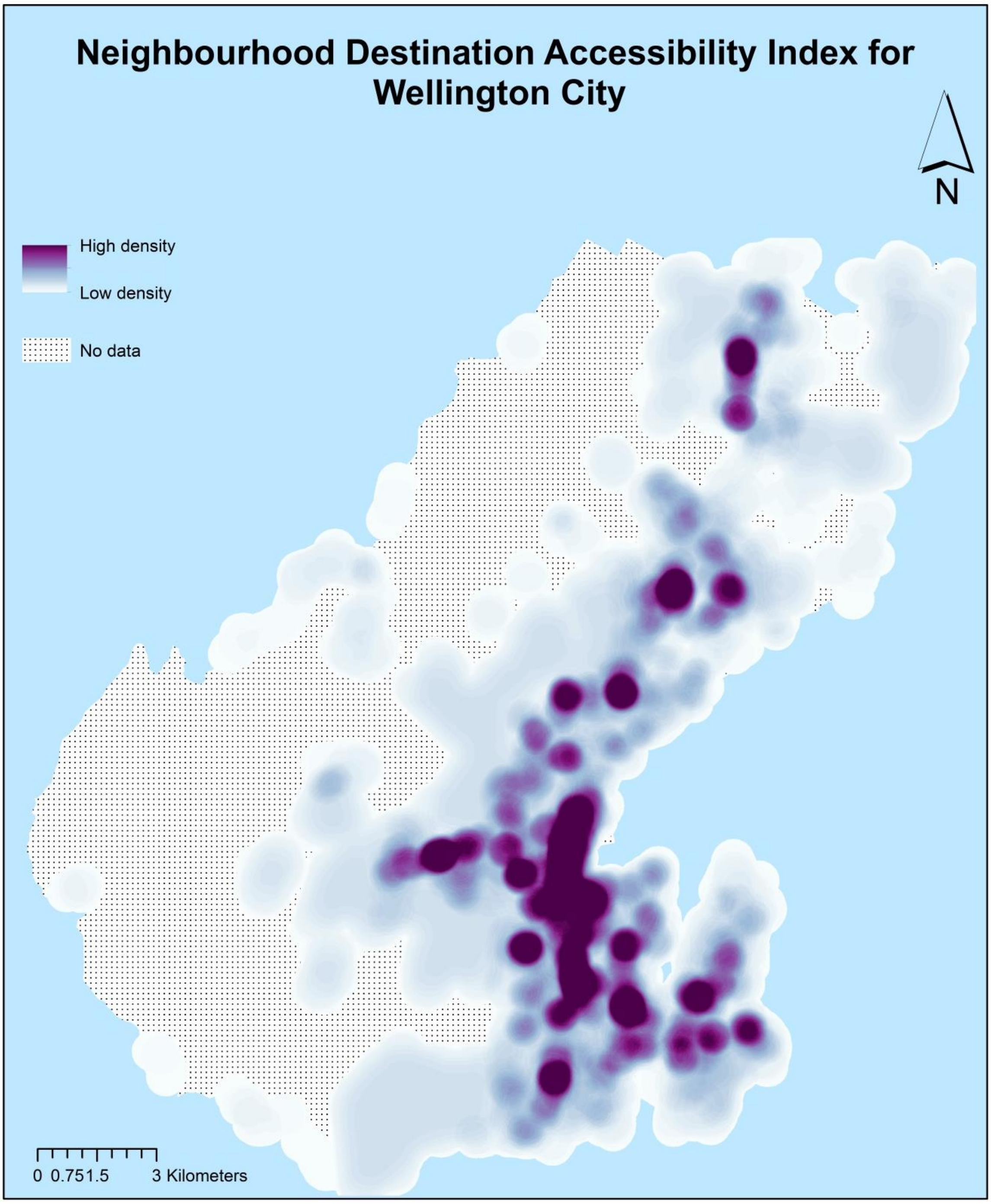


Figure 51. Kernel density map of Neighbourhood Destination Accessibility Index for Wellington City.

KDE values of the NDAI were then averaged to Euclidean (method 2) and network buffers (method 3) at three spatial scales, 800m, 1600m and 2400m based on meshblock population weighted centroids. The following sections give a brief description of the NDAIs based on methods 2 and 3 at the three spatial scales. Values range from 8 to 80, where values close to 80 indicate high destination accessibility and values close to 8 indicate low destination accessibility.

800m Neighbourhood level

Figures 52 and 53 present the density of destinations based on methods 2 (Euclidean) and 3 (network) at the 800m spatial level. Both methods show a high concentration of destinations in the city centre. The NDAI, based on method 3, displays a more disjointed pattern of destination density in comparison to method 2. In addition, the frequency distribution of data for method 2 is normally distributed, whereas the distribution of data in method 3 is slightly right skewed (positive).

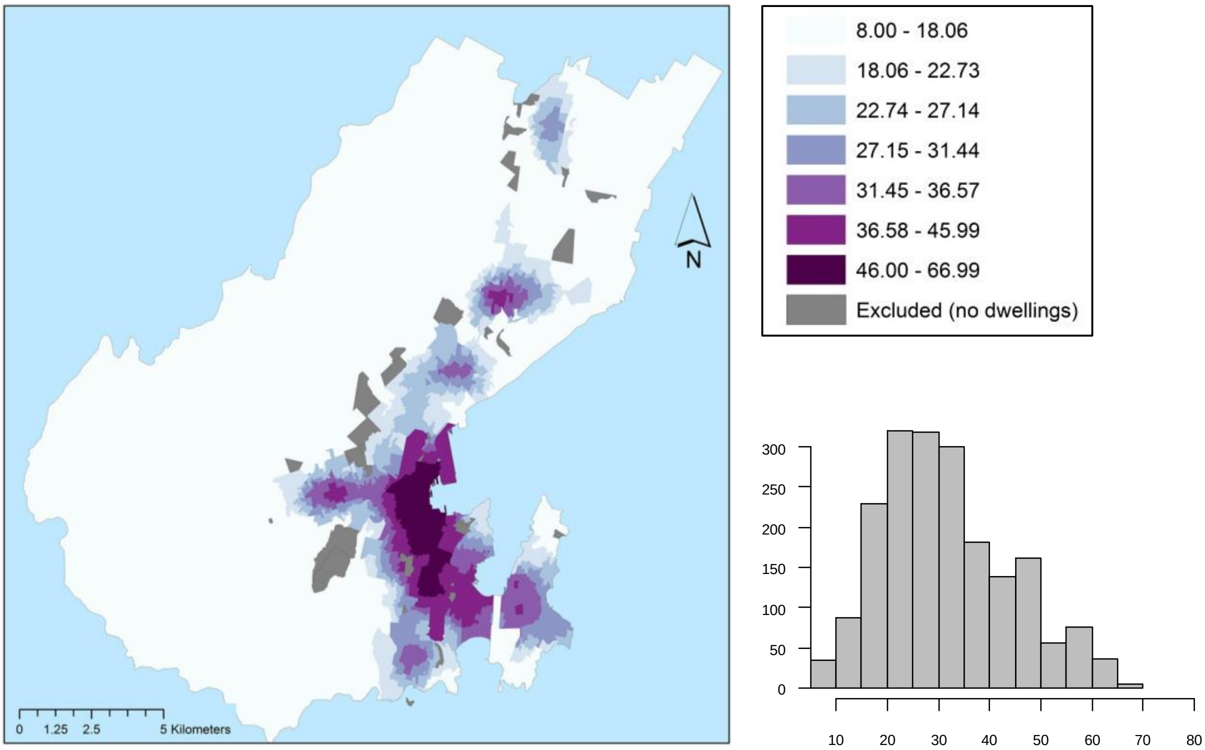


Figure 52. NDAI novel method, Euclidean buffer around PWCs, 800m (method 2).

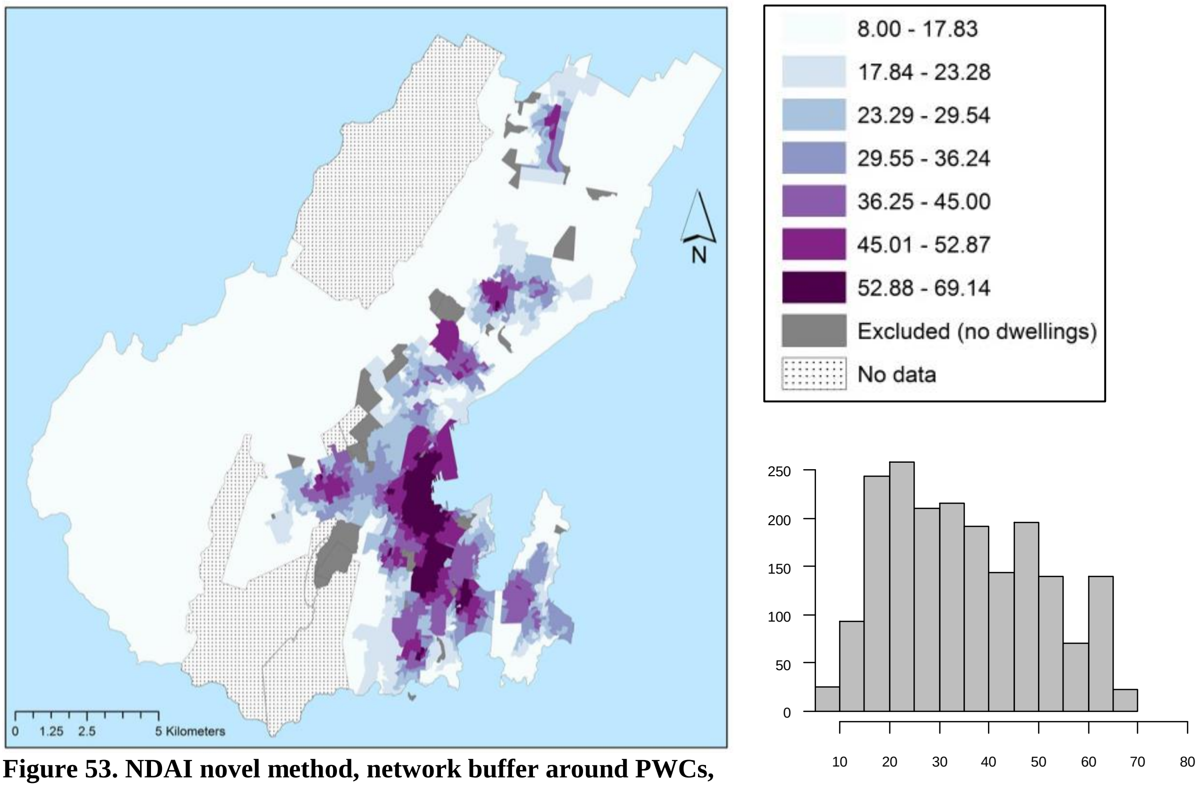


Figure 53. NDAI novel method, network buffer around PWCs, 800m (method 3).

1600m Neighbourhood level

Similar to the walk and bike indices (BWIs, EWIs and BIs) described previously, circular patterns of destination density emerge at the 1600m spatial scale for the NDAI based on method 2 (Euclidean buffer, Figure 54). In contrast, the NDAI based on method 3 (network buffer, Figure 55) has a more clustered and disjointed pattern. Both methods have similar normal distribution of underlying data.

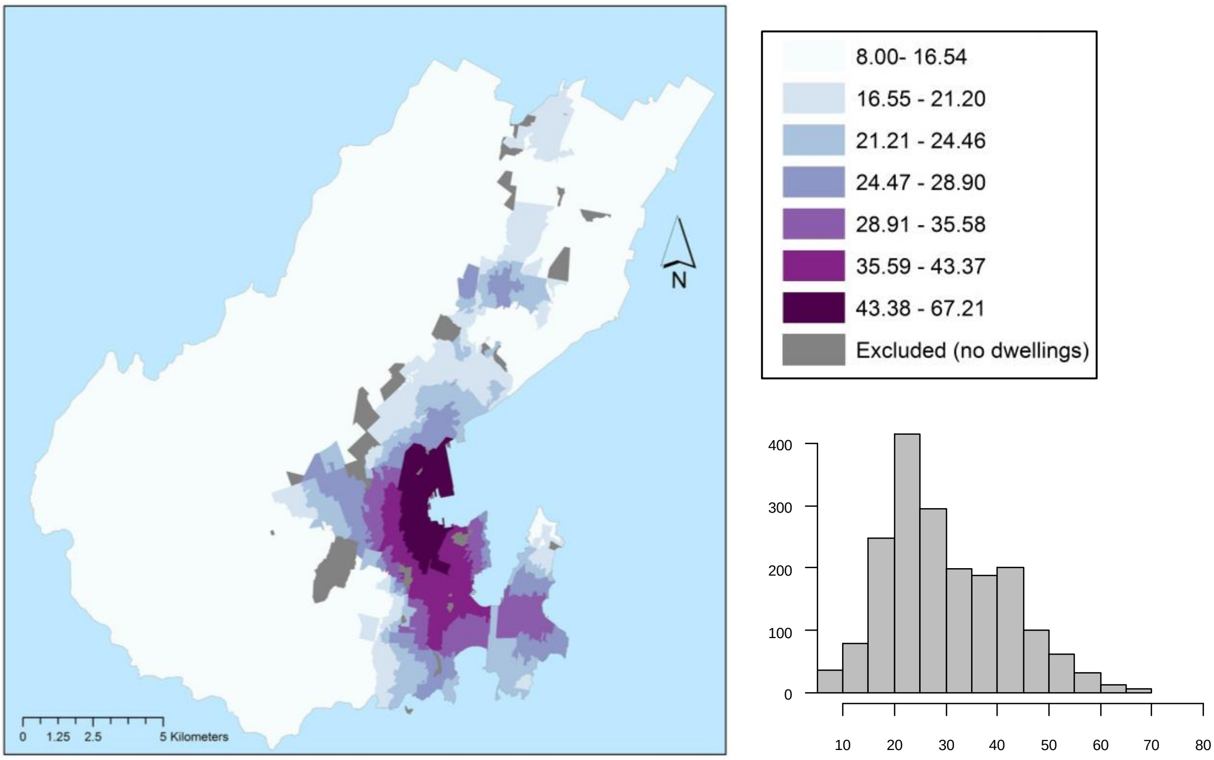


Figure 54. NDAI novel method, Euclidean buffer around PWCs, 1600m (method 2).

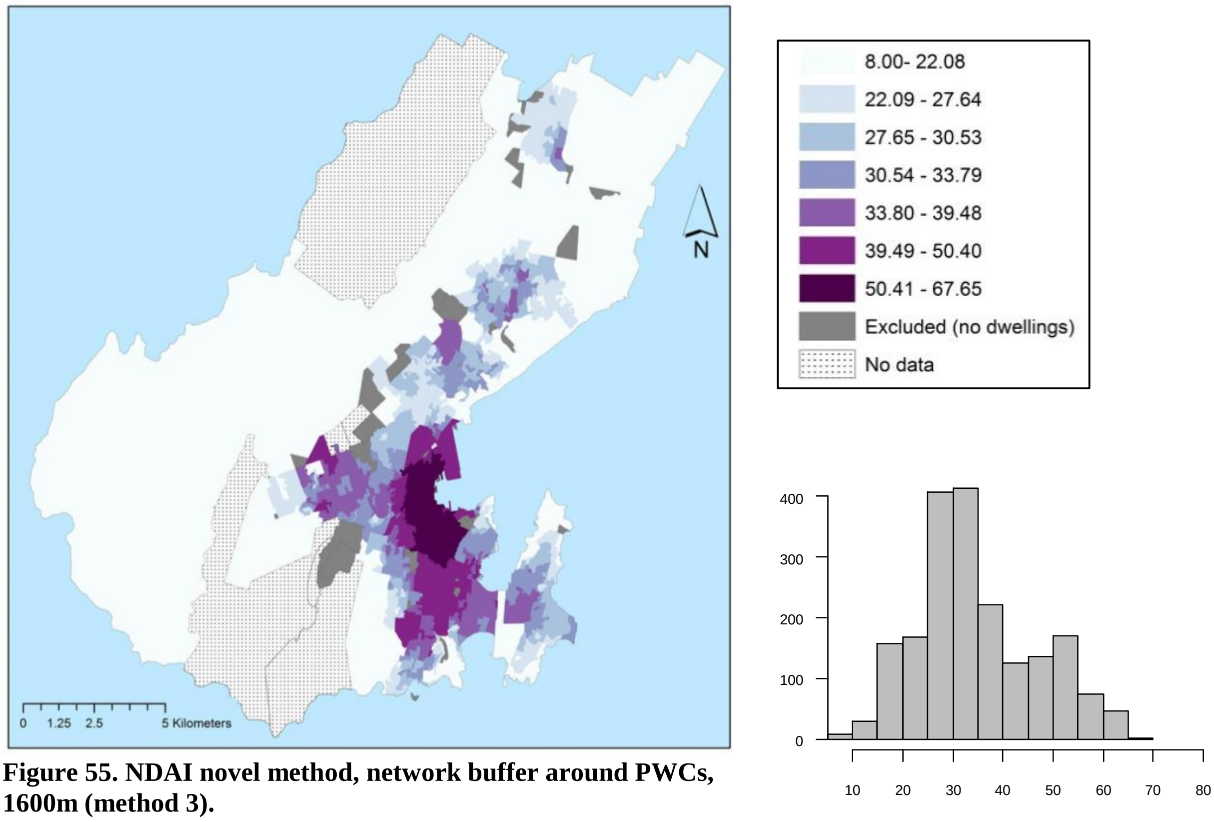


Figure 55. NDAI novel method, network buffer around PWCs, 1600m (method 3).

2400m Neighbourhood level

The NDAI based on method 2 at 2400m, has similar circular patterns of destination density originating in the city centre (Figure 56). In contrast, the NDAI based on method 3 has a separated pattern, reflecting the form of the network buffers (Figure 57). Method 2 has a slightly right skewed data distribution, in comparison, method 3 has a normal distribution of underlying data.

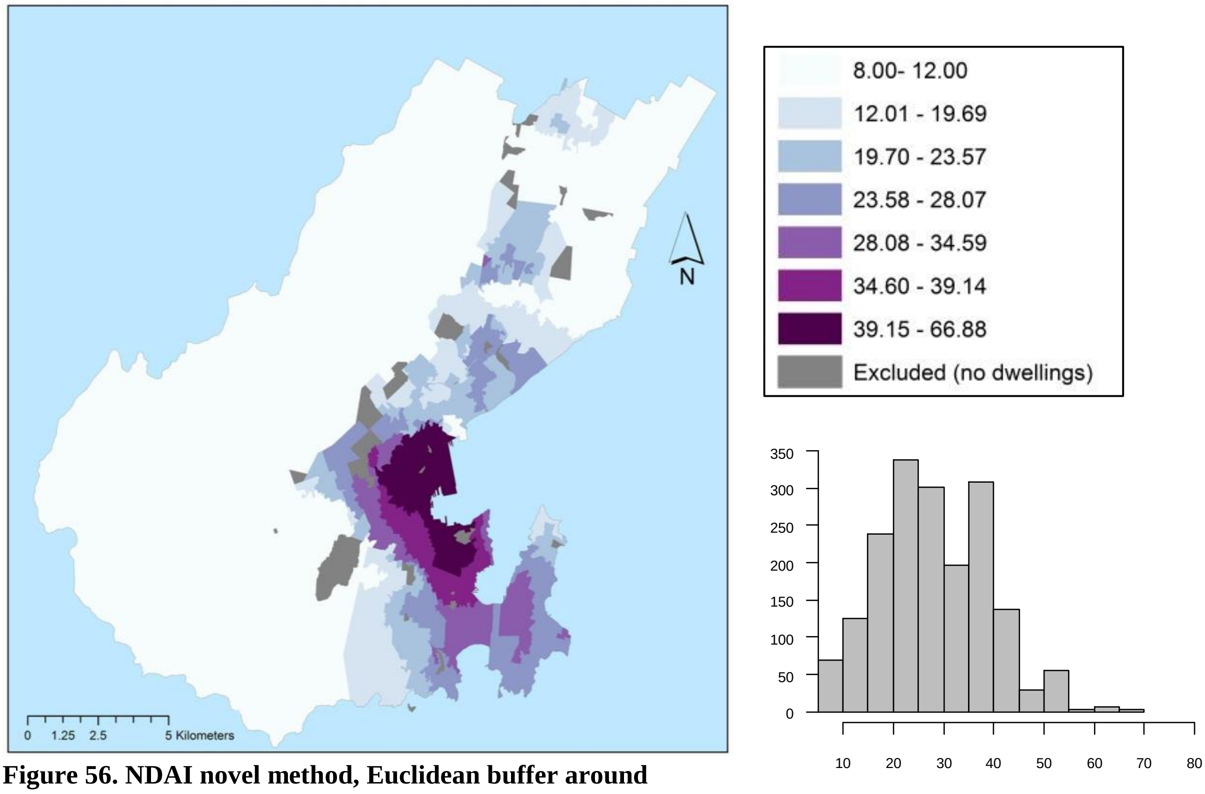


Figure 56. NDAI novel method, Euclidean buffer around PWCs, 2400m (method 2).

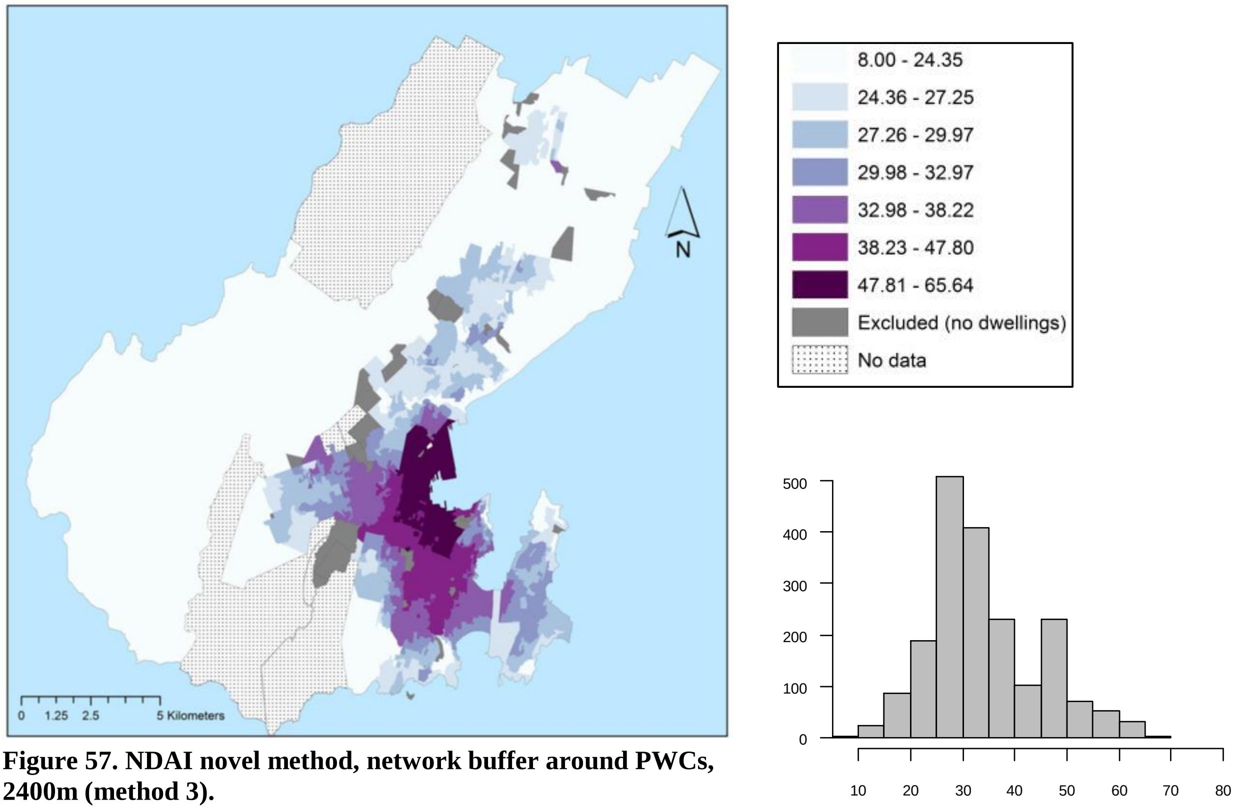


Figure 57. NDAI novel method, network buffer around PWCs, 2400m (method 3).

Summary statistics of each NDAI based on methods 2 and 3 at 800m, 1600m and 2400m, are presented in Table 13. Similar to the BI based on method 3, values were higher for the NDAI based on method 3, across each spatial scale, in comparison to the NDAI based on method 2. Furthermore, mean values for both methods decreased as the spatial scale increased.

Table 13. Descriptive statistics of the Neighbourhood Destination Accessibility Indices using various methods and spatial levels.

	Min	Max	Mean	Median	Std.
800m					
NDAI (Method 2)	8.00	67.00	30.87	29.30	12.99
NDAI (Method 3)	8.00	69.15	34.63	33.17	15.4
1600m					
NDAI (Method 2)	8.00	67.21	28.33	26.02	12.87
NDAI (Method 3)	8.00	67.66	34.29	32.17	12.35
2400m					
NDAI (Method 2)	8.00	66.88	26.09	25.75	12.41
NDAI (Method 3)	8.00	65.65	33.37	31.22	11.39

Similar to the BIs, both methods 2 and 3 were highly correlated. The highest correlation between the methods was at 800m, 0.91 and decreased as the spatial scale increased, (0.72 at 2400m).

Table 14. Pearson's correlation of NDAI methods for 800m, 1600m and 2400m spatial scales, (α= 5%, p<0.001).

Neighbourhood Definition	NDAI (Method 2)	NDAI (Method 3)
800m		
NDAI (Method 2)	1.00	0.91
NDAI (Method 3)		1.00
1600m		
NDAI (Method 2)	1.00	0.83
NDAI (Method 3)		1.00
2400m		
NDAI (Method 2)	1.00	0.72
NDAI (Method 3)		1.00

Summary

Similar to the BI based on method 2, a circular pattern of destination density was found at the 1600m and 2400m spatial scales. In general, the data for both NDAIs based on methods 2 and 3, were normally distributed across all three spatial levels. In addition, correlations between both methods were relatively high, with the highest correlation at 800m. Both NDAIs, based on 2 and 3 are investigated for associations with active transport, physical activity and health outcomes in Chapters 5, 6 and 7.

4.5 Conclusion

This chapter provided a brief description of each of the built environment indices (BWIs, EWIs, BIs and NDAIs) developed as part of this research. Standard (method 1) and novel (methods 2 and 3) were compared across three spatial levels, 800m, 1600m and 2400m. Further, the methods (Euclidean and network based buffers) were represented at the meshblock level, which is a new way of visualising the mean KDE values of the composite indices aggregated to two different buffers. Distinct circular patterns emerged for all indices based on method 2 (Euclidean buffer), whereas a more separated pattern was found all indices based on method 3 (network buffer) at 1600m and 2400m.

Each of the indices, based on methods 1, 2 and 3, will be investigated and validated through regression analysis using the New Zealand Household Travel Survey (NZHS, Chapter

5), Census (Chapter 6) and New Zealand Health Survey (HS, Chapter 7). The following chapter utilises individual level data from the NZHS and investigates the sensitivity of individual and composite measures of walkability (BWIs and EWIs based on methods 2 and 3) with time spent walking.

Chapter 5: Measuring Associations between Individual Attributes and Indices of the Built Environment and Time Spent Walking

5.1 Introduction

The overall goal of this research is to create composite indices of the built environment that characterise walking and cycling behaviours, and neighbourhood destination accessibility for Wellington City. Understanding how individual elements of the built environment can enable or hinder physical activity remains necessary in order to identify areas that could be modified to facilitate physical activity and potentially lead to improved health outcomes at a population level. The previous chapter examined the spatial variations between the Basic Walk Indices (BWIs), Enhanced Walk Indices (EWIs), Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs) across three spatial scales, 800m, 1600m and 2400m. The following three chapters test the validity of these indices, through statistical analyses using three different surveys, New Zealand Household Travel Survey (HTS), the Census and the New Zealand Health Survey (NZHS), comprised of active transport behaviours and health outcomes.

This chapter addresses the eighth objective of this thesis, which is to test the sensitivity of individual attributes separately, and together, in the form of composite indices, and their associations with active transport behaviours. It is an exploratory pilot study and serves as a sensitivity analyses for Chapters 6 and 7, which focus solely on the associations between the composite indices of the built environment and active travel behaviours and health outcomes.

5.2 Methods

Study data

The New Zealand Household Travel Survey (HTS) was used to validate and test associations between individual attributes, and composite indices of the built environment and time spent walking in Wellington City. The survey is carried out throughout the year, obtaining information on how, where and when people travel. Travel behaviour data is available continuously from 2003-2014, and a new travel survey using GPS and online forms began in 2015 (Ministry of Transport, 2016). Every one in seven households are randomly selected for inclusion in the survey, from meshblocks within each region around the country. Meshblocks are typically used to represent neighbourhoods in New Zealand, as they are the smallest geographic unit representing approximately 110 people (Statistics New Zealand, 2002).

Following a letter and visit by an interviewer describing the aims and content of the survey, participants are requested to report their travel behaviour throughout two consecutive, randomly assigned 'travel days'. Following the 'travel days' the interviewer returns and completes a personal interview with each member of the household. The information gathered includes, for example: household information such as household structure, relationship of people in the house, number of people, type and make of vehicles; individual person information such as age, sex, employment, income, ethnicity, marital status, driving experience, number of road crashes, location of workplace/school and destinations; and trip based information, such as trip purpose, mode choice, date, time, origin and destination. A full description of the variables and methods are available from Ministry of Transport, (2016). This research was interested in testing associations between travel behaviour and indices derived for Wellington City; as such, the sample was restricted to meshblocks from Wellington City.

Individual participant's address data for the HTS was obtained from the Ministry of Transport in May 2015. Even though data was available on multi-modal and multi-trip legs, this research was specifically concerned with testing associations between elements of the built environment and single, direct trips from home addresses to final destinations and therefore excluded multi-model trips. Importantly, sample sizes for the whole country each year ranged from 2,200 households from 2003/04 to 2007/08 (inclusive) to 4,600 households from 2008/09 onwards. Due to the small sample size for Wellington City, multiple years were combined in order to increase the sample size. Five years of data were combined, between 2009 and 2014.

Initially, the HTS dataset was filtered (in Excel) by transport mode (walk, cycle, public transport and car), trip start, (the home address), and trip purpose or destinations, (the work address). However, even after combining multiple years, the sample sizes of direct trips by walkers and cyclists from home to work were relatively small (Table 15). Therefore, a decision was made to include walking trips from home to any destination, which included work, education, shopping, social welfare, personal business, medical/dental, social visits/entertainment and recreational. In addition, the number of cyclists that cycled from home directly to work or any destination was deemed too small (n=44) to include in any exploratory analyses with the Bikeability Indices, which is examined in Chapters 6 and 7. As shown in Table 15, the majority of the participants in the sample drove directly from home to work (n=404) or any destination (including work, n=2,357). However, because active transport modes and their relationship with the built environment are the focus of this research, this examination was concerned solely with single trips originating at the home address and finishing at any destination, directly via an active transport mode and excluded public transport users and drivers. Therefore, only individuals that walked from home directly to any destination were included in the subsequent exploratory analyses.

Table 15. Sample sizes of the transport mode used leaving from the home address directly (without any multi-mode trips) to work or any destination in Wellington City.

Mode of transport	Home to work	Home to any destination (including work)
	(n)	(n)
Total trips by foot	81	133
Total trips by bike	9	44
Total trips by public transport	28	60
Total trips by car	404	2357

The home and destination addresses were geocoded in ArcGIS, (version 10.2) and the individual level travel behaviour data was attached to the neighbourhood level exposures of the built environment (BWIs, EWIs and NDAIs). The following sections describe the outcome variables of interest, possible confounders and briefly, the methods used to create the built environment exposure variables, (BWIs, EWIs and NDAIs) employed in these analyses.

5.2.1 Time spent walking to any destination

In order to compare findings with similar research that tested associations between attributes of the built environment and active commuting two outcomes based on the duration (in minutes) of walking trips to any destination were included in the analyses (Mackenbach et al., 2016). Although, Mackenbach et al., (2016) specifically used multi-walk trips from home to work, this sample is comprised of direct trips from home to work destinations which makes up 61 percent of total destinations. The first outcome was defined as individual walking trips from home to any destination for a duration of up to 10 minutes. Previous research has measured the availability in terms of count of destinations within a 720 metre network buffer of a tract centroid, generally representing locations within a 10 minute walk (Berke et al., 2007; Lee and Moudon, 2006; Moudon et al., 2007). The data was filtered to select individuals that only walked up to 10 minutes and a binary categorical variable was created, 1 = walked up to 10 minutes, 0 = did not walk up to 10 minutes. In addition, the second outcome, total duration of walking trips (in minutes), was included as a continuous variable.

5.2.2 Individual level covariates- demographic and socio-economic variables

Similar to previous research on the built environment and physical activity, (e.g. Witten et al., 2012; Pearson et al., 2014; Mackenbach et al., 2016) a number of demographic and socio-economic variables were included in the analyses to control for potential confounding. Individual age of each participant was gathered in the HTS. Several age groups, similar to Witten et al., (2012), were created as categorical variables in order to represent individuals at different stages of their lives. The groups created were 0-14, 15-29, 30-44, 55-64 and over 65 year olds. Sex and ethnicity were also included as a categorical variables. Three ethnic groups were identified in the sample data, European/Other, Māori and Asian. In addition, employment was categorised into five groups, 1) employed (full and part-time), 2) unemployed/looking for work, 3) full or part-time student, 4) unemployed, not looking for work (retired/keeping house), 5) Other (not yet at school/don’t know).

5.2.3 Area level covariate- neighbourhood deprivation

The New Zealand Index of Deprivation, 2013, (NZDep13) is an area level measure of deprivation, comprised of nine variables from the 2013 New Zealand Census. This index is regularly used to control for potential area level confounding in analyses on the built environment and physical activity (Witten et al., 2012; Pearson et al., 2014). The index is comprised of a number of elements hypothesised to represent deprivation in a population; as described in Table 16, this includes access to the internet, equivalised household income, means tested benefits, employment, single parent families, qualifications, home ownership, access to a car and household overcrowding (Atkinson et al., 2014).

Table 16. The 2013 New Zealand Index of Deprivation, (sourced from Atkinson et al., 2014).

Dimension of deprivation	**Description of variable (in order of decreasing weight in the index)**
Communication	People aged <65 with no access to the Internet at home
Income	People aged 18-64 receiving a means tested benefit
Income	People living in equivalised* households with income below an income threshold
Employment	People aged 18-64 unemployed
Qualifications	People aged 18-64 without any qualifications
Owned home	People not living in own home
Support	People aged <65 living in a single parent family
Living space	People living in equivalised* households below a bedroom occupancy threshold
Transport	People with no access to a car
*Equivalisation: methods used to control for household composition.	

Figure 58 is a map of area deprivation for Wellington city, showing that the city centre has higher deprivation than the surrounding suburbs, with darker meshblocks indicating higher deprivation.

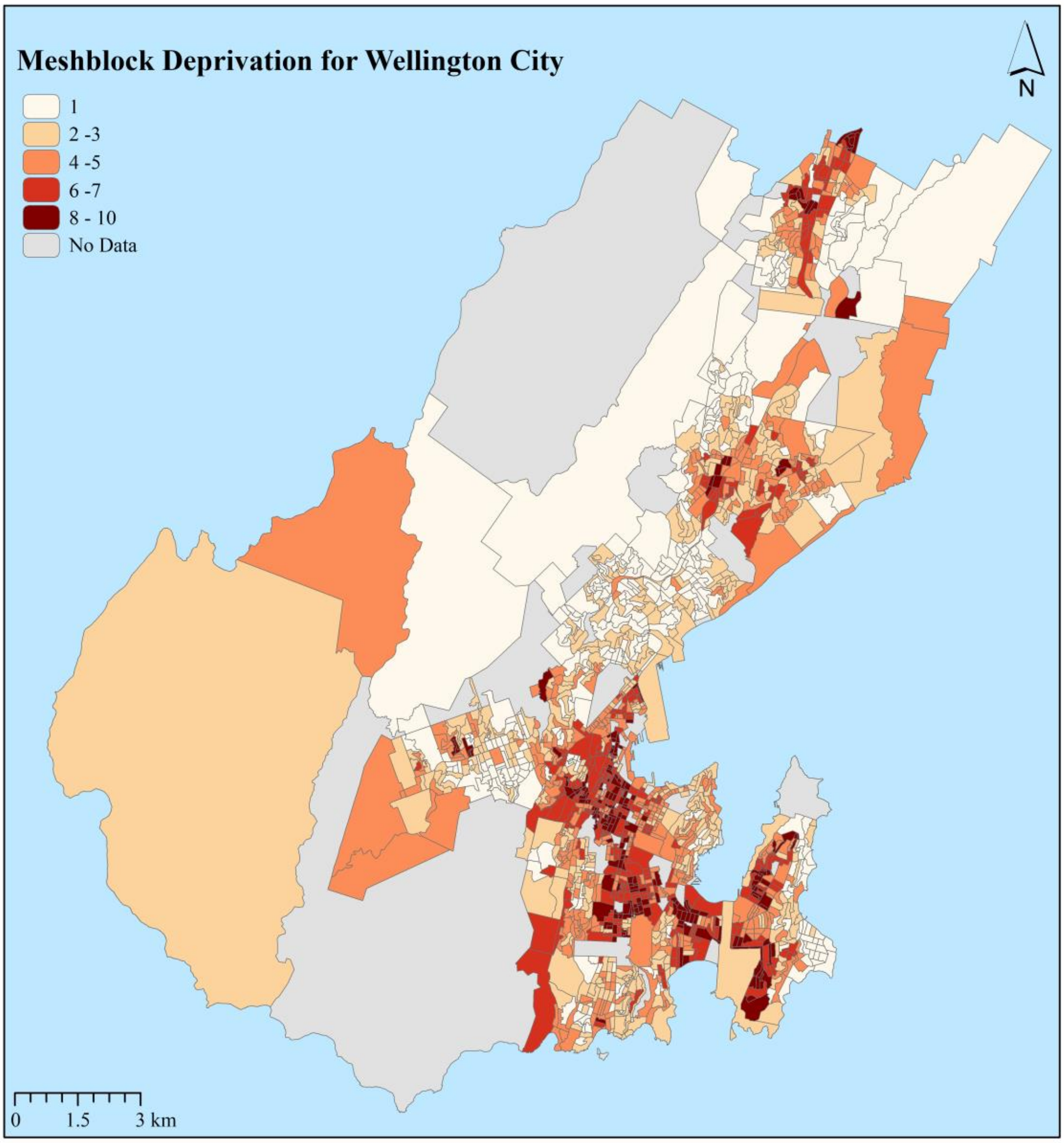


Figure 58. Measure of deprivation for the Wellington City, where areas that are darker reflect high deprivation. Note: NZDep was only calculated for areas that had addresses of buildings, (n=1,098), and areas with no address points were not analysed.

5.2.4 Built environment exposure measures

The kernel density based individual measures of the built environment, land use mix, street connectivity, dwelling density, slope, street lights and footpaths and tracks, based on methods 2 and 3, (described in Chapter 3), were included in this analyses with time spent walking. In addition, the composite indices measuring walkability, the BWI, comprised of land use mix, street connectivity and dwelling density and the EWI, comprised of slope, street lights and footpaths and tracks in addition to the BWI components, and the NDAI, comprised of densities of health, transport, education, retail, other retail, greenspace, financial and social cultural destinations, were also included as exposure measures. This chapter examines the relationship between the kernel density estimation (KDE) based measures only and active transport behaviours, the standard BWI is investigated in Chapters 6 and 7. It is important to note that the methods and neighbourhood scales described in Chapter 3 were slightly altered in this analyses in order to take advantage of the available individual address point data from the HTS. The two novel methods described in Chapter 3 consisted of KDE based built environment elements aggregated to (vector) Euclidean (method 2) and network (method 3) buffers around population weighted centroids (PWCs) at 800m, 1600m and 2400m. In contrast, methods 2 and 3 applied in this chapter, utilised individual address points, rather than PWCs, to create a number of additional buffers (400m, 800m, 1200m, 1600m, 2000m and 2400m), both Euclidean and network. Individual address points were unavailable for the subsequent chapters, due to restrictions on confidentially sensitive data, and thus PWCs were used as a proxy for individual addresses.

In addition and in contrast with subsequent chapters, this chapter investigates three aspects of the participant's built environment exposure:

1) the home environment, (the area around the home based on Euclidean and network buffers);
2) the route environment, (the most likely route taken from home to destination);
3) the destination environment, (the area around the destination walked to, based on Euclidean and network buffers).

Steps taken to create participant's built environment exposures

1) the residential home and destination addresses were geocoded.
2) Euclidean and network buffers of 400m, 800m, 1200m, 1600m, 2000m and 2400m were created.
3) The most likely route, based on the road network and distance (in metres), was generated using the *closest facility tool* from the *Network Analyst* suite in ArcGIS (10.2).
4) Buffers of 50m and 100m from the road centreline between the home and destination address were created. Routes were created for participants that walked directly from home to any destination (n=133).
5) Following KDE of the individual attributes and standardising into deciles, as with methods 2 and 3, (the Euclidean and network buffers; described in detail in Chapter 3, Section 3.6.2), each of the attributes were computed into the *zonal statistics as table*. Values were averaged to the Euclidean and network buffers

around the home and destination addresses at 400m, 800m, 1200m, 1600m, 2000m and 2400m and the route buffers between home and destination (50m and 100m) in ArcGIS (10.2).

This method provided the average density of participant's exposure to measures of the built environment, both individual and indices, in their home, destination and along their hypothetical route environments. Figure 59 is an example of a route with a 50m and 100m buffer from a participant's home to a destination with the underlying KDE of dwelling density before entering the values into the *zonal statistics as table* model. As described in Chapter 4, section 4.2, (Table 7), each of the BWIs and EWIs based on methods 2 and 3 (Chapter 3, section 5.6.2) were rescaled in order to conduct statistical analyses with exposure data based on the same scale.

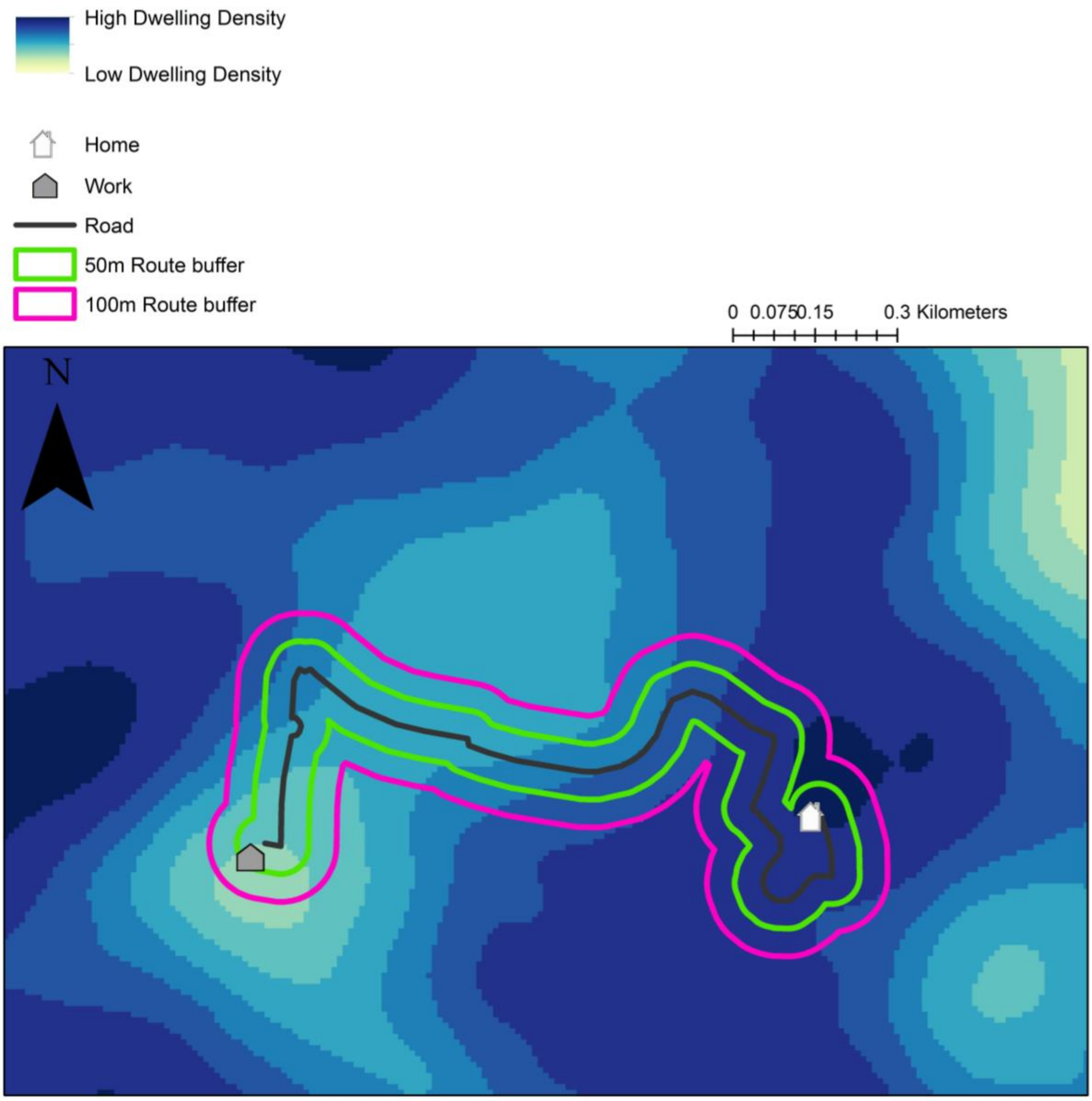


Figure 59. Example of kernel density estimation of dwelling density along the route, including 50m and 100m buffers, between home and destination.

5.3 Statistical analyses

Summary statistics were calculated for the outcome variables and each of the individual index components and overall composite BWIs and EWIs. The next section describes the statistical analyses methods applied to test associations between the built environment exposures and time spent walking to any destination.

All analyses of the exposure measures in the three environments, home, destination and route were analysed separately, similar to previous research by Witten et al., (2012) and Mackenbach et al., (2016). Separate logistic regression models were used to explore associations between attributes and indices of the built environment, for multiple neighbourhoods around participant's home and destination, (both Euclidean and network at a range of spatial scales 400m, 800, 1200m, 1600m) and along the route (50m and 100m buffers), and the outcome variable, walking up to 10 minutes to any destination. Individuals were categorised as 1, walking up to 10 minutes to any destination or 0, not walking up to 10 minutes to any destination. Logistic regression based on the binomial exponential family of distribution (UCLA, 2016) was used to investigate associations. Coefficients were exponentiated in order to report the odds ratios and confidence intervals (95%) were also computed.

Similar to Mackenbach et al., (2016) total duration (in minutes) was included as a sensitivity analysis with repeated measures and additional distances. The continuous variable, total duration (in minutes) was analysed using individual generalized linear regression models (GLM) with log link and based on the Gamma distribution. The GLMs were utilised to test associations between elements of the built environment at various spatial levels 400m, 800m, 1200m, 1600m, and additionally 2000m and 2400m (as the maximum distance walked for total duration outcome variable was 2400m). Coefficients were exponentiated enabling interpretation of results, where a unit increase in the exposure measures was associated with the percentage change in time spent walking (95% confidence intervals also computed).

Finally, both the binomial logistic and GLM regression models were additionally adjusted for age, sex and ethnicity (Model 2) and employment and area deprivation (Model 3), (Table 17). Results for models 1, 2 and 3 are reported for the outcome variable, walking up to 10 minutes, and only results for the fully adjusted model (3) of total duration spent walking are reported, as it serves as a sensitivity analyses. In addition, self-selection was not included in this analyses as previous research in New Zealand did not find any associations between neighbourhood choice, the built environment and time spent walking for transport, leisure or all purposes (Witten et al., 2012).

Table 17. Example table of multiple models applied to test for associations between outcome and exposure variables using binomial logistic regression models.

Outcome variables [a]	**Model 1 [a]: Unadjusted bivariate models**	**Model 2 [b]: Adjusted for demographics**	**Model 3 [b]: Adjusted for socio-economic and area deprivation**
Up to 10 minutes walking from home to any destination	***Exposure variables** run as individual models and tested using various buffers around the home, destination and route* - Land use mix - Street connectivity - Dwelling density - Slope - Street lights - Footpaths and tracks - BWIs - EWIs - NDAIs (methods 2 & 3)	***Exposure variables** run as individual models and tested using various buffers around the home, destination and route* - Land use mix - Street connectivity - Dwelling density - Slope - Street lights - Footpaths and tracks - BWIs - EWIs - NDAIs (methods 2 & 3)	***Exposure variables** run as individual models and tested using various buffers around the home, destination and route* - Land use mix - Street connectivity - Dwelling density - Slope - Street lights - Footpaths and tracks - BWIs - EWIs - NDAIs (methods 2 & 3)
		Age: - 0-15 - 45-54 - 15-29 - 55-64 - 30-44 - ≥65	**Age:** - 0-15 - 45-54 - 15-29 - 55-64 - 30-44 - ≥65
		Ethnicity: - Māori -Asian -European/Other	**Ethnicity:** - Māori -Asian -European/Other
		Sex: -Female -Male	**Sex:** -Female -Male
			Employment: - Employed, full and part-time - Unemployed, looking for work - Student, full and part-time - Unemployed, not looking for work (retired/keeping house) - Other
			NZ Deprivation: - Quintile 1 - Quintile 2 - Quintile 3 - Quintile 4 - Quintile 5

[a] The second outcome variable, total duration (in minutes) spent walking from home to any destination was also tested for associations using a generalised linear model with gamma distribution and log link for each of the individual component and composite measures (BWIs, EWIs and NDAIs). [b] The second outcome (total duration) was additionally controlled for potential confounders in models 2 and 3.

5.4 Results

The following section describes the results of the descriptive statistics and regression analyses. Then both the unadjusted and adjusted results for up to 10 minutes spent walking (section 5.4.2, and 5.4.3), and the fully adjusted results for total time spent walking (section 5.4.4) and the relationship with the measures of the built environment are presented.

5.4.1 Descriptive characteristics of outcomes, covariates and built environment measures

Table 18 presents the summary statistics of the two outcomes of interest and distance travelled. The average duration of walking trips up to 10 minutes was 7.83 minutes (Std=2.89), and the average distance travelled was 540m (Std=30m) with a maximum of 1310m. In contrast, the average total time spent walking to a destination was 16.35 minutes (Std=10.39), and the average distance travelled was 950m (Std=610m). The maximum of total time spent walking was 60 minutes and a distance of 2490m. Due to the maximum distance travelled by individuals walking for up to 10 minutes, only neighbourhood scales in increments of 400m, from 400m up to 1600m were analysed. Neighbourhood scales from 400m up to 2400m were included for total time spent walking as the maximum distance walked by individuals was 2490m.

Table 18. Summary statistics of outcome variables; walking up to 10 minutes and total duration spent walking. Distance travelled for each outcome also included.

Summary Statistics	Walked up to 10 minutes (minutes)	Total time spent walking (minutes)	Distance travelled up to 10 minutes (kilometres)	Distance travelled total duration (kilometres)
Minimum	1.00	1.00	0.01	0.01
Median	10.00	15.00	0.48	0.87
Mean (Std)	7.83 (2.89)	16.35 (10.39)	0.54 (0.30)	0.95 (0.61)
Maximum	10.00	60.00	1.31	2.49

The socio-demographic characteristics of the HTS sample are presented in Table 19. The total number of individuals that walked directly from home to any destination was n=53, of that group 41.5% were under 15 years of age, with the 15-29 year olds making up the second highest group at 20.75%. In contrast, the total number of participants for total time spent walking was n=133, again the highest age group was under 15 (32.8%) and the 15-29 year olds second highest (20.9%). Both outcome variables, up to 10 minutes and total time spent walking, had a higher percentage of males to females, 60.4% vs. 39.6% and 57.9% vs. 42.1% respectively. There were strong differences in the percentage of ethnic groups for each outcome. Māori had the smallest percentage for walking up to 10 minutes, 15.1%, and were the largest group, 68.4%, in the overall total time spent walking to a destination. In contrast, Europeans were the dominant group for walking up to 10 minutes, 58.5% and far behind second highest after Māori in total time spent walking, 18%. Up to 45.3% of participants walking up to 10 minutes were full or part-time students, whereas 34% were employed (full or part-time) and 22.6% were unemployed, not looking for work. In comparison to total time spent walking, 40% were employed (full or part-time), 38% were students (full or part-time) and 22% unemployed, not looking for work. Finally, less than 8% of the sample that walked up to 10 minutes and 9% of total time spent walking lived in the least deprived neighbourhoods (Quintile 1), whereas 28.3% and 21.8% respectively, lived in the second most deprived areas (Quintile 4). While most of the sample, for both outcomes, walking up to 10 minutes and total time spent walking to a destination, were in the middle quintile, 50.9% and 49.6% respectively.

Table 19. Sample characteristics of the walkers in Household Travel Survey between 2009 and 2014.

Covariates	Time spent walking: Walked up to 10 minutes	Time spent walking: Total time spent walking
Total (n)	**53**	**133**
Age (%)		
0-14	41.51	32.84
15-29	20.75	20.90
30-44	9.43	11.19
45-54	9.43	10.45
55-64	5.67	10.45
≥65	13.21	14.18
Sex (%)		
Female	39.62	42.11
Male	60.38	57.89
Ethnicity (%)		
Māori	15.09	68.42
Asia	24.53	13.53
European	58.49	18.04
Missing n=1		
Employment* (%)		
Employed, full and part-time	33.96	39.85
Unemployed, looking for work	0	1.50
Student, full and part-time	45.28	37.59
Unemployed, not looking for work (retired/keeping house)	22.64	21.80
Other	1.89	3.01

Table 19. continued.

New Zealand Deprivation Index 2013 (%)	Walked up to 10 minutes %	Total time spent walking %
Q1 (Least deprived)	7.55	9.02
Q2	9.43	18.05
Q3	50.94	49.63
Q4	28.31	21.80
Q5 (Most deprived)	3.77	1.50

*percentage is over 100 as some individuals counted twice, for example, a part time student with a part time job

The mean and standard deviations of each individual and composite index exposure measure (standardised to deciles) for the home and destination addresses, both Euclidean and network, at 400m, 800m, 1200m, 1600m, 2000m and 2400m are presented (Tables 49 and 50 in Appendix A). In addition, the summary statistics for each individual and composite measure (standardised to deciles) along the route, between home and destination at 50m and 100m buffers are also presented (Table 51, Appendix A).

5.4.2 Associations of individual attributes of the built environment and walking trips up to 10 minutes

As mentioned previously, this is an exploratory study, and the results should be interpreted with caution, due to the small sample size. This section investigates associations between individual elements of the built environment and time spent walking. Individual measures, standardised to deciles were utilised in the subsequent analysis. The following research questions were used to guide the examination:

A) Are individual built environment characteristics associated with walking from home to any destination for up to 10 minutes?

B) Do results vary depending on 1) buffer delineation around the home, destination or along the route and 2) spatial scale?

The results of model 1, with unadjusted bivariate associations between individual and composite attributes of the built environment, and walking to a destination for up to 10 minutes are presented (Table 20). These results show associations between the built environment, measured as both Euclidean and network buffers at 400m, 800m, 1200m and 1600m around the home and destination addresses, and walking trips for up to 10 minutes. The results of associations between the exposure measures, and routes are presented (Table 21). Binomial regression models with exponentiated coefficients were applied in this analysis in order to report the odds ratios. Values greater than 1 indicate a positive association between walking for up to 10 minutes and a measure of the built environment. Model 2 was additionally adjusted for individual age, sex and ethnicity. Similarly, model 3 was adjusted adjustments for income, employment and area deprivation.

Table 20. Separate, unadjusted binomial logistic regression models of associations between individual and composite measures of the built environment and walking up to 10 minutes for neighbourhood buffers, Euclidean and network, around the home and destination addresses at 400m, 800m, 1200m and 1600m buffers. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Model 1**							
	400m		**800m**		**1200m**		**1600m**	
Home address Euclidean buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.04	(0.87-1.25)	1.07	(0.84-1.37)	1.21	(0.81-1.83)	1.28	(0.65-2.55)
Street connectivity	1.17	(0.94-1.51)	1.28	(0.98-1.73)	1.42	(1.01-2.09)	1.51	(1.00-2.37)
Dwelling density	1.20	(0.96-1.56)	**1.47***	**(1.05-2.20)**	1.49	(1.02-2.31)	1.31	(0.92-1.90)
Slope	**1.19***	**(1.04-1.37)**	1.29	(0.99-1.68)	1.37	(0.93-2.03)	**1.48***	**(1.00-2.20)**
Street lights	**1.34***	**(1.03-1.82)**	**1.39***	**(1.04-1.94)**	**1.42***	**(1.04-2.01)**	1.31	(0.97-1.78)
Footpaths and tracks	1.60	(0.91-3.25)	1.89	(1.04-4.25)	1.88	(1.06-3.96)	1.62	(0.95-2.97)
BWI	1.05	(0.94-1.18)	**1.14***	**(1.01-1.29)**	**1.17***	**(1.04-1.32)**	1.10	(0.98-1.24)
EWI	**1.25*****	**(1.10-1.42)**	**1.20****	**(1.07-1.37)**	**1.14***	**(1.01-1.28)**	1.12	(0.99-1.26)
NDAI	1.49	(1.02-2.27)	**1.77***	**(1.10-3.19)**	**1.80***	**(1.12-3.21)**	**1.58***	**(1.07-2.39)**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 20. continued.

Up to 10 minutes spent walking	**Model 1**							
	400m		**800m**		**1200m**		**1600m**	
Home address network buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.04	(0.88-1.24)	1.04	(0.86-1.26)	1.07	(0.83-1.37)	1.20	(0.85-1.69)
Street connectivity	1.19	(0.95-1.56)	1.29	(0.99-1.75)	1.30	(0.95-1.82)	1.31	(0.91-1.94)
Dwelling density	1.22	(0.97-1.60)	**1.41***	**(1.06-1.95)**	1.34	(0.99-1.88)	1.34	(0.95-1.95)
Slope	**1.18****	**(1.05-1.33)**	**1.28****	**(1.08-1.54)**	**1.35****	**(1.08-1.70)**	**1.35***	**(1.05-1.75)**
Street lights	**1.35***	**(1.04-1.83)**	**1.36***	**(1.04-1.84)**	**1.39***	**(1.03-1.95)**	1.40	(1.01-2.02)
Footpaths and tracks	1.49	(0.81-3.22)	1.88	(0.90-4.82)	2.34	(0.95-6.99)	2.66	(0.98-9.03)
BWI	1.04	(0.93-1.17)	**1.19****	**(1.05-1.35)**	**1.13***	**(1.01-1.28)**	**1.14***	**(1.01-1.28)**
EWI	**1.21****	**(1.08-1.38)**	**1.21****	**(1.07-1.37)**	**1.19****	**(1.06-1.35)**	**1.17****	**(1.05-1.33)**
NDAI	1.35	(0.97-1.93)	1.54	(1.02-2.46)	**1.83***	**(1.08-3.37)**	**2.01***	**(1.14-3.98)**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 20. continued.

Up to 10 minutes spent walking	**Model 1**							
	400m		**800m**		**1200m**		**1600m**	
Any destination address Euclidean buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.86	(0.69-1.07)	**0.70***	**(0.51-0.96)**	0.77	(0.49-1.19)	0.99	(0.55-1.80)
Street connectivity	**1.45***	**(1.12-2.02)**	**1.39***	**(1.07-1.92)**	**1.40***	**(1.05-1.95)**	1.34	(0.99-1.87)
Dwelling density	**1.63*****	**(1.28-2.18)**	**1.55****	**(1.19-2.09)**	**1.45***	**(1.10-1.97)**	1.30	(0.97-1.76)
Slope	1.04	(0.87-1.23)	0.91	(0.71-1.17)	0.84	(0.58-1.20)	1.03	(0.66-1.58)
Street lights	**1.44****	**(1.16-1.84)**	**1.39****	**(1.11-1.78)**	**1.32***	**(1.05-1.70)**	1.23	(0.97-1.58)
Footpaths and tracks	**3.60****	**(1.72-9.35)**	**2.43***	**(1.35-5.27)**	**2.25****	**(1.31-4.39)**	**1.78***	**(1.13-2.95)**
BWI	1.04	(0.93-1.17)	1.11	(0.98-1.25)	**1.13***	**(1.00-1.28)**	1.09	(0.97-1.23)
EWI	**1.21****	**(1.07-1.38)**	**1.15***	**(1.02-1.30)**	**1.16***	**(1.03-1.31)**	1.12	(0.99-1.27)
NDAI	**1.65***	**(1.12-2.74)**	**1.66***	**(1.13-2.66)**	**1.63***	**(1.14-2.45)**	**1.45***	**(1.07-2.01)**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 20. continued.

Up to 10 minutes spent walking	**Model 1**							
	400m		**800m**		**1200m**		**1600m**	
Any destination address network buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.95	(0.78-1.16)	0.92	(0.72-1.17)	0.91	(0.68-1.20)	0.88	(0.62-1.24)
Street connectivity	1.29	(1.01-1.77)	1.22	(0.94-1.67)	1.15	(0.86-1.60)	1.11	(0.80-1.60)
Dwelling density	**1.53****	**(1.20-2.04)**	**1.49****	**(1.14-2.05)**	**1.39***	**(1.05-1.93)**	1.31	(0.96-1.85)
Slope	1.12	(0.97-1.30)	1.05	(0.87-1.25)	1.03	(0.82-1.28)	1.08	(0.83-1.39)
Street lights	**1.34***	**(1.07-1.73)**	**1.35***	**(1.05-1.79)**	1.28	(0.98-1.72)	1.23	(0.93-1.66)
Footpaths and tracks	**2.98***	**(1.41-8.42)**	**2.46***	**(1.24-6.41)**	**2.98***	**(1.32-8.97)**	**2.66***	**(1.13-7.82)**
BWI	1.06	(0.94-1.19)	1.10	(0.98-1.24)	1.08	(0.96-1.22)	1.09	(0.97-1.23)
EWI	**1.23****	**(1.09-1.40)**	**1.14***	**(1.01-1.29)**	1.11	(0.98-1.26)	1.09	(0.97-1.23)
NDAI	1.43	(1.02-2.25)	1.42	(0.99-2.31)	1.33	(0.89-2.16)	1.34	(0.86-2.21)

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 21. Separate, unadjusted binomial regression models of associations between individual and composite measures of the built environment and walking up to 10 minutes for buffers along the route from home to destination at 50m and 100m. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Model 1**			
Route buffer	**50m**		**100m**	
	OR	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.14	(0.93-1.42)	1.13	(0.91-1.40)
Street connectivity	1.33	(1.01-1.89)	1.31	(1.00-1.86)
Dwelling density	**1.53****	**(1.15-2.17)**	**1.51****	**(1.14-2.14)**
Slope	**1.19***	**(1.04-1.37)**	**1.19***	**(1.03-1.38)**
Street lights	**1.39***	**(1.08-1.85)**	**1.40***	**(1.08-1.87)**
Footpaths and tracks	**4.19***	**(1.53-16.68)**	**3.69***	**(1.43-13.39)**
BWI	**1.24*****	**(1.10-1.41)**	**1.25***	**(1.10-1.42)**
EWI	**1.23****	**(1.09-1.40)**	**1.20****	**(1.06-1.37)**
NDAI	**1.62***	**(1.12-2.56)**	**1.60***	**(1.10-2.51)**

Values highlighted in bold indicate statistically significant associations,
 * =p<0.05, ** =p<0.01 and *** =p<0.001.

Land use mix

In the unadjusted model, (model 1, Table 20), land use mix did not show any associations with walking up to 10 minutes around home addresses, with the Euclidean or network buffers across any neighbourhood scales, (400m, 800m, 1200m and 1600m). However, it was significantly and negatively associated with walking up to10 minutes at the 800m neighbourhood around destinations, with the use of Euclidean buffer only. While in the positive direction, (greater than 1), there was no significant association between land use mix along routes from home to destinations and up to 10 minutes spent walking, with both the 50m and 100m buffers (Table 21).

After adjusting for age, sex and ethnicity in model 2, (Table 22), the models failed to reach statistical significance for both the Euclidean and network buffers around the home addresses. In model 1, there was a statistically significant negative association only the 800m spatial level based on the Euclidean buffer around the destination, this remained after adjusting for potential confounders in model 2, however, the OR decreased from 0.70 to 0.68, where the likelihood of walking up to 10 minutes was negatively associated with a unit increase in land use mix. Moreover, similar to model 1, there was no association between land use mix and destinations based on the network buffer at any scale. Regarding the route between home and destination, no association remained between land use mix and walking up to 10 minutes, after adjusting for covariates (Table 23).

In model 3, (Table 24), after additionally adjusting for employment and area deprivation, no association remained for Euclidean and network buffers around the home addresses. However, a significant negative association remained between land use mix around the destination addresses based on the Euclidean buffer at 800m and walking up to 10 minutes. In addition, no association was found for both the network buffer around destinations and the route between home and destination (Table 24) and walking up to 10 minutes across any spatial level.

Street connectivity

The results of model 1, (Table 20), show that there were no associations between street connectivity, for either the Euclidean or network buffer around home addresses at any neighbourhood level (400m, 800m, 1200m and 1600m). However, in relation to destinations, there was a significant positive association between walking up to 10 minutes and street connectivity at 400m, 800m and 1200m with Euclidean defined neighbourhoods with OR 1.45, 1.39 and 1.40 respectively. In contrast, there was no association between the network defined neighbourhood around the destinations and walking up to 10 minutes. In relation to routes from home addresses to destinations and street connectivity, no significant association was found. However, the ORs were in the expected direction for both the 50m and 100m, but failed to reach statistical significance, (Table 21).

After adjusting for age, sex and ethnicity in model 2, (Table 22), there was still no association between street connectivity and the neighbourhoods around the home address, both Euclidean and network, at any spatial level. Nevertheless, street connectivity around the destination, based on the Euclidean buffer, remained significantly positively associated with walking up to 10 minutes at 400m and 800m only, with 1200m failing to remain statistically significant. However, similar to model 1, there was no association found for the network based buffer around the destinations or the route between home and destination at any spatial level (Table 23).

In the fully adjusted model, (Table 24 and Table 25), no associations remained between density of street connectivity and walking up to 10 minutes at either the home, (both Euclidean and network buffers) or along the route at any spatial level. This finding shows the strong negative confounding effect of employment and area deprivation on walking up to 10 minutes and street connectivity. However, street connectivity was statistically significant at 400m only, (Euclidean buffer) around destinations where the odds of walking up to 10 minutes increased by 37% for every unit increase in street connectivity. Creating built environments with highly connected streets could potentially increase short walking trips.

Dwelling density

The results of model 1, (Table 20), show that 800m was the only spatial level significantly positively associated with walking up to 10 minutes in both the Euclidean and network defined neighbourhoods around the home. In addition, the ORs were similar, where an increase in dwelling density in the Euclidean defined neighbourhood was associated with 47% increase in the odds of walking up to 10 minutes, and 41% increased odds in the network defined neighbourhood around home addresses. In addition, dwelling density around the destination neighbourhoods had a significant positive association with walking up to 10 minutes at 400m, 800m and 1200m, both with Euclidean and network buffers. The ORs were highest for 400m, Euclidean buffer, OR1.63, network buffer, OR 1.53, and decreased as the spatial levels increased, with 1200m decreased to Euclidean OR1.45 and network OR1.39. Likewise, dwelling density along the route (Table 21) between home addresses and destinations, with both 50m and 100m buffers, showed significant positive associations with walking up to 10 minutes, OR1.53 and OR1.51 respectively.

In model 2, after adjusting for demographic covariates (Table 22), dwelling density around the home address, based on the Euclidean buffer, did not remain significant at 800m, and no association was found across all spatial levels. However, it did remain significantly associated with walking up to 10 minutes at 800m based on the network buffer around the home address, with ORs increasing marginally from 1.41-1.43. In relation to dwelling density around the destination address based on the Euclidean and network buffers, significant positive associations between walking up to 10 minutes remained at 400m, 800m (network only) and 1200m (Euclidean). In addition, for both the Euclidean and network buffers, the 400m neighbourhood around the destination address had the strongest ORs, 1.75 and 1.58, respectively. Significant associations remained in model 2 with ORs slightly improved for dwelling density along the route and walking up to 10 minutes (Table 23).

After additionally adjusting for employment and area deprivation (model 3, Table 24), no association remained between dwelling density and walking up to 10 minutes at any spatial level around the home address for the Euclidean buffers. However, a significant positive association remained between dwelling density at the 800m network buffer around the home and walking. In addition, the ORs improved, where the odds of walking up to 10 minutes to a destination increased by 53% for a unit increase in dwelling density around the home. Density of dwellings around the destination address remained significantly positively associated with walking up to 10 minutes for both the Euclidean buffers at 400m, 800m and 1200m and the network buffers at 400m and 800m only. Furthermore, statistically significant associations remained between dwelling density and walking along the route environment remained (Table 25).

Areas with higher density of dwellings around the home environment, (800m based on the Euclidean buffer) and the destination environments, both Euclidean and network, can potentially predict increased short walking trips to any destination. In addition, a high density of dwellings along the route could also encourage short walking trips.

Slope

Similar to all the other individual attributes of the built environment, the slope measure was standardised into deciles. However, unlike the other measures, the values were then inverted, whereby a value of 10 equalled low slope density and 1 equalled high slope density, therefore ORs greater than 1, indicate lower slope density. In model 1, (Table 20) low density of slope was statistically significant and positively associated with the Euclidean defined neighbourhood around home addresses at 400m and 1600m spatial levels only. However, at the network defined neighbourhood around home addresses, low slope density was significantly positively associated with walking up to 10 minutes across all spatial levels, (400m, 800m, 1200m and 1600m). Therefore, the lower the slope around home addresses, the higher the odds of walking up to 10 minutes with ORs ranging from OR1.18 at 400m increasing to OR1.35 at 1600m. This association reveals that low slope may be a factor impacting positively in the decision to walk for up to 10 minutes around homes in Wellington. Conversely, there was no association between the Euclidean or network defined neighbourhoods around destinations and slope density, for any spatial level. However, there was a significant positive association between the density of slope along the route from home addresses to destinations and walking up to 10 minutes (Table 21). At both the 50m and 100m buffer along the route (Table 21), low slope density was significantly associated with increased odds of walking, OR 1.19 and OR 1.19, respectively. This finding indicates that the slope along the route can influence whether a person decides to walk to a destination or not.

After adjusting for age, sex and ethnicity, model 2, (Table 22), low density of slope remained significantly associated with walking up to 10 minutes around the home address based on the Euclidean buffer at 400m and 1600m, but also became significant at 800m and 1200m. In addition the effect sizes of the ORs increased from moderate to strong as spatial scale increased, from OR1.37 at 400m to OR2.06 at 1600m. In addition, low density of slope remained significantly positively associated with walking around the home based on the network buffer across all spatial levels. ORs ranged from 1.33 at 400m to 1.64 at 1600m. However, no association between walking up to 10 minutes and density of slope was found for either the Euclidean or network buffers around the address points. In contrast, density of slope along the route from home to destination remained significantly associated with walking up to 10 minutes even after adjusting for covariates, OR1.29 (both 50m and 100m buffers), (Table 23).

Model 3 was additionally adjusted for employment and area deprivation, (Table 24). Results show that low slope density, only at the 1600m spatial level around the home address (Euclidean buffer), remained significantly associated with walking for up to 10 minutes. In addition the ORs improved, where low slope density around the home at 1600m was associated with an increase in walking by a factor of 2.26 (CI 1.07-5.05). In contrast, only the 400m network buffer around home addresses remained significantly associated with walking, OR1.26, (CI 1.01-1.61). Similar to model 2, there was no association between slope density around the destination addresses, for both the Euclidean and network buffers and walking up to 10 minutes. In addition, no association remained between slope along the route from home to destination and walking up to 10 minutes (Table 25).

Density of low slope around the home environment was found to be associated with walking up to 10 minutes at 400m for the network buffer and 1600m for the Euclidean buffer. These results indicate the potential importance of considering slope as a factor that can influence whether or not people walk short trips from their residential home environment.

Street lights

The results of model 1, presented in Table 20, show that street light density around home addresses for both the Euclidean and network buffers was positively associated with walking up to 10 minutes at 400m, 800m, and 1200m. Effect sizes were moderate with ORs similar for both the Euclidean and network defined neighbourhoods around home addresses and ranged from OR 1.34 and OR 1.35 at 400m to OR 1.42 and OR 1.39 at 1200m, respectively. Likewise, street light density around destinations with Euclidean neighbourhoods at 400m, 800m and 1200m and the network defined neighbourhoods at 400m and 800m only, were statistically significant and positively associated with walking up to 10 minutes. For example, an increase in street light density at the 400m levels was associated with a 44% (Euclidean) and 34% (network) increased odds of walking up to 10 minutes. Furthermore, in Table 21, the density of street lights along the route between home addresses and destinations showed a significant positive association with walking up to 10 minutes, with both the 50m and 100m buffers (OR 1.39 and OR 1.40 respectively).

In model 2, (Table 22), after adjusting for demographic covariates, density of street lights around the home address for both Euclidean and network buffers did not remain significantly associated with walking up to 10 minutes, indicating possible negative confounding. In contrast, positive associations remained between walking up to 10 minutes and street light density around the destination address, for the Euclidean buffers at 400m, 800m and 1200m and only the 800m network buffer. ORs were strongest for the Euclidean buffer as opposed to the network buffer, where an increase in street light density around destinations was associated with a 52% (Euclidean, 400m and 800m) and 35% (network, 400m) increased likelihood of walking up to 10 minutes. After adjusting for covariates, density of street lights along the route from home to destination remained significantly associated with walking, however the ORs remained the same, indicating no confounding effect of the covariates, (Table 23).

In model 3, after additionally adjusting for employment and area deprivation, (Table 24), there was still no association between street light density around the home environment, both Euclidean and network buffers, and walking up to 10 minutes. However, a significant positive association continued between density of street lights and walking in the Euclidean defined neighbourhoods at 400m and 800m only around destinations. However, in contrast to model 2, no association was found between street light density for the network buffer around destinations and along the route with time spent walking (Table 25).

These results could indicate the utility of measuring the destination environment rather than focusing solely on the home environment to predict associations with walking. The results could also reflect the common tendency of street lights in urban areas where destinations such as cafés, restaurant and parks are located. Having street lights at destinations could potentially encourage people to walk short distances from their home environments.

Footpaths and tracks

The results of model 1, (Table 20) showed there was no association between density of footpaths and tracts around home addresses, at the Euclidean defined neighbourhood at any level and walking up to 10 minutes. Even though the ORs were in the expected direction, greater than 1, no significant statistical association was found. In addition, the results were similar for the network defined neighbourhoods, with no association found for all spatial levels. However, footpath and track density around destinations, both with Euclidean and network buffers, was significantly positively associated with walking up to 10 minutes across all spatial levels 400m, 800m, 1200m and 1600m. In addition, the effect sizes were strong, showing that an increase of footpath and track density at 400m was associated with an increased odds of walking up to 10 minutes by factor of 3.60 (Euclidean) and 2.98 (network). Although the ORs decreased as the size of neighbourhoods increased, the effect sizes remained strong, OR1.78, Euclidean, 1600m and OR2.66, network, 1600m. Furthermore, the density of footpaths and tracks along the route between home addresses and destinations was significantly positively associated with walking up to 10 minutes for both the 50m and 100m buffers, and effect sizes were very strong, OR4.19 and OR3.69 respectively (Table 21).

After adjusting for age, sex and ethnicity in model 2, (Table 22), no association remained between footpaths and tracks around the home addresses, both Euclidean and network, and walking up to 10 minutes. However, in relation to density of footpaths and tracks around destinations (Euclidean buffers), ORs remained significantly positively associated with time spent walking, and had improved effect sizes for all spatial levels. The highest OR was found at the 400m neighbourhood scale around the destination (Euclidean buffer), where an increase in footpath and track density was associated with an increase in odds of walking up to 10 minutes by a factor of 4.26. In relation to the network buffer around destinations, associations remained at 400m and 1200m only, with 1200m scale having the strongest effect size, OR2.94. Regarding the relationship between footpath and track density along the route and walking up to 10 minutes, strong, positive, significant associations remained for 50m buffer only, however the ORs reduced from 4.19 to 3.59, indicating possible negative confounding (Table 23).

In model 3, after also adjusting for employment and area deprivation, (Table 24), no association between footpath and track density and walking up to 10 minutes in the home environment, for both the Euclidean and network buffers, at any spatial scale. In relation to footpath and track density around the destinations, associations remained for the Euclidean defined neighbourhoods at 400m, 800m and 1200m only. Although effect sizes reduced after controlling for employment and area deprivation, ORs were again strongest at the 400m scale, where the odds of walking up to 10 minutes from home to a destination increased by a factor of 3.91 per unit increase in footpath and track density around destination addresses. In contrast, no associations remained for the network defined neighbourhoods around destinations. However, statistically significant positive associations remained along the route environment (Table 25) between home and destinations and footpath density. Remarkably, the odds of walking up to 10 minutes increased by a factor of 4.64 (50m) and 4.09 (100m), per unit increase in footpath and track density.

These findings are interesting and could suggest that footpath and track density are not as important around the home environment as the destination and route environments. Ensuring footpaths and tracks are available around destinations and along the route could encourage short walking trips. This finding lends to the growing discussion about the need to consider objectively measuring the built environment around destinations and the route environment rather than the commonly focused residential home environment.

Table 22. Separate, binomial logistic regression models, adjusted for age, sex and ethnicity, of associations between individual and composite measures of the built environment and walking up to 10 minutes for neighbourhood buffers, Euclidean and network, around the home and destination addresses at 400m, 800m, 1200m and 1600m buffers. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Model 2 (adjusted for age, sex and ethnicity)**							
	400m		**800m**		**1200m**		**1600m**	
Home Address Euclidean Buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.12	0.91-1.38	1.18	0.88-1.58	1.38	0.87-2.26	1.37	0.65-2.99
Street connectivity	1.13	0.89-1.49	1.20	0.89-1.65	1.30	0.89-1.96	1.46	0.92-2.44
Dwelling density	1.21	0.92-1.65	1.40	0.97-2.18	1.47	0.95-2.46	1.41	0.91-2.24
Slope	**1.37****	**1.13-1.68**	**1.61****	**1.14-2.32**	**1.87***	**1.14-3.16**	**2.06****	**1.23-3.58**
Street lights	1.34	0.99-1.91	1.32	0.96-1.91	1.42	0.99-2.15	1.42	0.99-2.10
Footpaths and tracks	1.43	0.77-3.15	1.63	0.87-3.75	1.69	0.90-3.79	1.60	0.86-3.30
BWI	1.04	0.921.18	1.12	0.98-1.29	**1.16***	**1.01-1.33**	1.10	0.96-1.26
EWI	**1.29*****	**1.12-1.51**	**1.21****	**1.06-1.40**	1.14	0.99-1.31	1.13	0.99-1.30
NDAI	1.58	0.98-2.52	1.69	1.00-0.24	**1.84***	**1.07-3.55**	**1.94***	**1.18-3.39**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 22. continued.

Up to 10 minutes spent walking	**Model 2 (adjusted for age, sex and ethnicity)**							
	400m		**800m**		**1200m**		**1600m**	
Home address network buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.10	0.91-1.34	1.10	0.88-1.38	1.16	0.87-1.55	1.38	0.93-2.09
Street connectivity	1.15	0.90-1.54	1.23	0.92-1.70	1.23	0.88-1.79	1.22	0.82-1.88
Dwelling density	1.24	0.94-1.71	**1.43***	**1.04-2.09**	1.40	0.98-2.10	1.40	0.93-2.21
Slope	**1.33***	**1.13-1.60**	**1.52*****	**1.20-1.98**	**1.61****	**1.21-2.19**	**1.64****	**1.19-2.29**
Street lights	1.28	0.90-1.86	1.33	0.99-1.87	1.39	0.99-2.05	1.44	0.98-2.22
Footpaths and tracks	1.31	0.67-3.04	1.59	0.73-4.31	2.12	0.78-7.20	2.53	0.83-10.46
BWI	1.02	0.90-1.16	**1.19***	**1.04-0.38**	1.13	0.99-1.30	1.13	0.99-1.29
EWI	**1.25****	**1.09-1.46**	**1.24****	**1.08-1.44**	**1.21****	**1.06-1.39**	**1.18***	**1.04-1.36**
NDAI	1.40	0.97-2.14	1.55	0.97-2.66	1.91	1.06-3.89	**2.23***	**1.15-5.03**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 22. continued.

Up to 10 minutes spent walking	Model 2 (adjusted for age, sex and ethnicity)							
	400m		800m		1200m		1600m	
Any destination address Euclidean buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.86	0.67-1.09	**0.68***	**0.47-0.98**	0.74	0.43-1.26	1.03	0.51-2.09
Street connectivity	**1.45***	**1.08-2.07**	**1.40***	**1.03-2.02**	1.43	1.02-2.13	1.39	0.97-2.07
Dwelling density	**1.75*****	**1.32-2.43**	**1.70****	**1.24-2.45**	**1.64****	**1.16-2.41**	1.44	1.01-2.13
Slope	1.08	0.89-1.30	0.97	0.73-1.29	0.93	0.60-1.44	1.20	0.70-2.05
Street lights	**1.52****	**1.18-2.04**	**1.52****	**1.15-2.09**	**1.45***	**1.09-2.00**	1.34	0.99-1.83
Footpaths and tracks	**4.26****	**1.81-12.75**	**2.77***	**1.37-6.87**	**2.62***	**1.35-5.90**	**2.05***	**1.18-3.90**
BWI	1.01	0.88-1.15	1.12	0.97-1.29	**1.16***	**1.00-1.34**	1.11	0.97-1.29
EWI	**1.25****	**1.09-1.46**	**1.17***	**1.02-1.36**	**1.20***	**1.04-1.39**	**1.17***	**1.02-1.35**
NDAI	1.63	1.06-2.84	**1.83***	**1.13-3.27**	**1.93****	**1.23-3.27**	**1.73****	**1.17-2.68**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 22. continued.

Up to 10 minutes spent walking	**Model 2 (adjusted for age, sex and ethnicity)**							
	400m		**800m**		**1200m**		**1600m**	
Any destination address network buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.96	0.77-1.20	0.95	0.73-1.25	0.95	0.69-1.31	0.93	0.62-1.39
Street connectivity	1.23	0.95-1.71	1.15	0.86-1.61	1.07	0.76-1.56	1.04	0.70-1.57
Dwelling density	**1.58****	**1.20-2.22**	**1.53***	**1.13-2.23**	1.43	1.03-2.11	1.36	0.94-2.06
Slope	1.18	0.99-1.40	1.09	0.89-1.34	1.10	0.85-1.44	1.19	0.88-1.62
Street lights	**1.35***	**1.04-1.80**	1.34	1.00-1.88	1.31	0.95-1.87	1.29	0.92-1.86
Footpaths and tracks	**2.89***	**1.30-9.07**	2.25	1.08-6.32	**2.94***	**1.17-10.12**	2.75	1.02-9.75
BWI	1.02	0.89-1.16	1.11	0.97-1.28	1.09	0.95-1.25	1.09	0.95-1.26
EWI	**1.26****	**1.09-1.48**	1.14	0.99-1.31	1.10	0.96-1.27	1.11	0.97-1.27
NDAI	1.37	0.94-2.22	1.35	0.90-2.29	1.29	0.81-2.28	1.42	0.84-2.59

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 23. Separate, binomial regression models, adjusted for age, sex and ethnicity, of associations between individual and composite measures of the built environment and walking up to 10 minutes for buffers along the route from home to destination at 50m and 100m. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Route buffer (Model 2)**			
	50m		**100m**	
	OR	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.25	0.98-1.63	1.23	0.96-1.61
Street connectivity	1.24	0.94-1.80	1.23	0.93-1.78
Dwelling density	**1.54***	**1.12-2.28**	**1.53***	**1.11-2.27**
Slope	**1.29****	**1.09-1.54**	**1.29****	**1.09-1.56**
Street lights	**1.39***	**1.04-1.95**	**1.40***	**1.04-1.97**
Footpaths and tracks	**3.59***	**1.27-15.47**	**3.22***	**1.20-12.90**
BWI	**1.26****	**1.09-1.47**	**1.27****	**1.10-1.48**
EWI	**1.27****	**1.09-1.49**	**1.25****	**1.08-1.46**
NDAI	**1.57***	**1.06-2.58**	**1.55***	**1.04-2.57**

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 24 Separate, binomial logistic regression models, adjusted for age, sex and ethnicity, employment and area deprivation, of associations between individual and composite measures of the built environment and walking up to 10 minutes for neighbourhood buffers, Euclidean and network, around the home and destination addresses at 400m, 800m, 1200m and 1600m buffers. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Model 3 (adjusted for employment and area deprivation)**							
	400m		**800m**		**1200m**		**1600m**	
Home address Euclidean buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.97	0.73-1.28	0.99	0.68-1.44	1.09	0.62-1.95	0.99	0.41-2.40
Street connectivity	1.23	0.91-1.74	1.29	0.89-1.93	1.33	0.85-2.17	1.31	0.77-2.31
Dwelling density	1.37	0.95-2.16	1.53	0.97-2.70	1.45	0.86-2.66	1.25	0.74-2.17
Slope	1.26	0.99-1.65	1.25	0.81-1.95	1.46	0.78-2.76	**2.26***	**1.07-5.05**
Street lights	1.33	0.96-1.92	1.31	0.93-1.94	1.33	0.89-2.06	1.26	0.84-1.95
Footpaths and tracks	2.07	0.91-6.17	1.83	0.88-4.95	1.62	0.79-3.90	1.32	0.66-2.85
BWI	0.92	0.78-1.07	1.1	0.94-1.29	1.09	0.93-1.29	1.01	0.86-1.19
EWI	**1.28****	**1.08-1.53**	1.16	0.98-1.37	1.06	0.91-1.24	1.04	0.88-1.23
NDAI	1.43	0.89-2.44	1.63	0.88-3.43	1.57	0.83-3.33	1.49	0.83-2.83

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 24. continued.

Up to 10 minutes spent walking	Model 3 (adjusted for employment and area deprivation)							
	400m		800m		1200m		1600m	
Home address network buffer	OR	CI (95%)	OR	CI (95%)	OR	CI (95%)	OR	CI (95%)
Land use mix	0.95	0.72-1.24	0.93	0.69-1.25	0.91	0.61-1.34	1.07	0.65-1.78
Street connectivity	1.3	0.94-1.88	1.32	0.93-1.95	1.38	0.90-2.22	1.32	0.79-2.31
Dwelling density	1.46	1.00-2.34	**1.54***	**1.05-2.40**	1.52	0.97-2.51	1.38	0.82-2.47
Slope	**1.26***	**1.01-1.61**	1.32	0.99-1.81	1.36	0.98-1.92	1.38	0.95-2.04
Street lights	1.34	0.98-1.91	1.29	0.94-1.83	1.36	0.94-2.05	1.34	0.87-2.16
Footpaths and tracks	2.14	0.87-7.04	2.32	0.91-7.60	3.6	1.05-16.87	3.05	0.81-15.99
BWI	0.9	0.77-1.05	1.18	1.00-1.41	1.11	0.95-1.30	1.06	0.90-1.26
EWI	**1.23***	**1.05-1.47**	**1.22***	**1.03-1.46**	1.17	0.99-1.40	1.11	0.93-1.33
NDAI	1.31	0.87-2.03	1.32	0.79-2.32	1.75	0.89-3.80	1.89	0.86-4.83

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 24. continued.

Up to 10 minutes spent walking	Model 3 (adjusted for employment and area deprivation)							
	400m		800m		1200m		1600m	
Any destination address Euclidean buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.76	0.56-1.01	**0.52****	**0.32-0.81**	0.55	0.28-1.02	0.76	0.33-1.73
Street connectivity	**1.37***	**1.03-1.98**	1.38	0.99-2.02	1.39	0.96-2.10	1.29	0.87-1.98
Dwelling density	**1.67****	**1.23-2.42**	**1.64****	**1.18-2.43**	**1.53***	**1.05-2.31**	1.29	0.86-2.00
Slope	1.02	0.82-1.26	0.83	0.57-1.15	0.67	0.36-1.20	0.97	0.44-2.04
Street lights	**1.43***	**1.09-1.97**	**1.45***	**1.07-2.03**	1.37	0.99-1.93	1.23	0.88-1.75
Footpaths and tracks	**3.91***	**1.55-13.54**	**2.82***	**1.31-7.86**	**2.39***	**1.20-5.63**	1.81	0.97-3.67
BWI	0.9	0.76-1.04	1.08	0.92-1.26	1.11	0.95-1.31	1.07	0.91-1.27
EWI	**1.19***	**1.01-1.42**	1.12	0.95-1.32	1.16	0.99-1.37	1.13	0.96-1.34
NDAI	1.55	0.96-2.84	1.68	0.99-3.21	**1.76***	**1.04-3.24**	1.52	0.94-2.58

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 24. continued.

Up to 10 minutes spent walking	Model 3 (adjusted for employment and area deprivation)							
	400m		800m		1200m		1600m	
Any destination address network buffer	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	0.87	0.67-1.12	0.84	0.61-1.16	0.82	0.55-1.19	0.77	0.47-1.23
Street connectivity	1.23	0.94-1.72	1.17	0.86-1.67	1.09	0.74-1.65	1.04	0.67-1.67
Dwelling density	**1.48***	**1.10-2.15**	**1.45***	**1.06-2.15**	1.36	0.95-2.04	1.25	0.83-1.95
Slope	1.11	0.92-1.34	0.96	0.74-1.21	0.9	0.65-1.24	0.99	0.67-1.45
Street lights	1.26	0.96-1.71	1.25	0.92-1.77	1.21	0.86-1.76	1.2	0.83-1.78
Footpaths and tracks	**2.77***	**1.22-9.47**	**2.34***	**1.04-7.53**	**3.16***	**1.13-12.96**	2.82	0.94-11.20
BWI	0.91	0.77-1.06	1.05	0.90-1.23	1.02	0.88-1.19	1.01	0.86-1.19
EWI	1.18	0.99-1.41	1.08	0.92-1.26	1.02	0.87-1.20	1.04	0.89-1.22
NDAI	1.33	0.88-2.21	1.31	0.84-2.26	1.17	0.70-2.14	1.16	0.63-2.30

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 25. Separate, binomial regression models, adjusted for age, sex and ethnicity, employment and area deprivation, of associations between individual and composite measures of the built environment and walking up to 10 minutes for buffers along the route from home to destination at 50m and 100m. Odds ratios and confidence intervals (95%) are presented.

Up to 10 minutes spent walking	**Route buffer (Model 3)**			
	50m		**100m**	
	OR	**CI (95%)**	**OR**	**CI (95%)**
Land use mix	1.14	0.84-1.55	1.11	0.82-1.52
Street connectivity	1.29	0.95-1.93	1.29	0.94-1.91
Dwelling density	**1.44***	**1.04-2.20**	**1.45***	**1.04-2.25**
Slope	1.19	0.98-1.47	1.19	0.97-1.48
Street lights	1.31	0.97-1.85	1.32	0.97-1.87
Footpaths and tracks	**4.64***	**1.34-28.14**	**4.09***	**1.27-22.95**
BWI	**1.22***	**1.03-1.47**	**1.24***	**1.04-1.49**
EWI	**1.24***	**1.04-1.49**	**1.24***	**1.04-1.49**
NDAI	1.43	0.95-2.35	1.42	0.94-2.34

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

5.4.3 Associations of indices of walkability and neighbourhood destination accessibility and walking trips up to 10 minutes

This section examines associations between the rescaled composite indices of the built environment, BWIs and EWIs, (as discussed in Chapter 4, Table 7) and NDAIs with time spent walking. The following research questions were used to guide the analyses:

A) Are indices of walkability (BWIs and EWIs) and neighbourhood destination accessibility associated with walking from home to any destination for up to 10 minutes?

B) Do results vary depending on 1) buffer delineation around the home, destination or along the route and 2) spatial scale?

Basic Walk Index

The results of the BWI (comprised of the measures land use mix, street connectivity and dwelling density) in model 1 are presented in Table 21. The BWI was significantly positively associated with walking up to 10 minutes at 800m and 1200m around the home, based on the Euclidean defined neighbourhoods. The ORs were highest at 1200m, where a unit increase in walkability (BWI) was associated with a 17% increased odds of walking up to 10 minutes. Similarly, the walkability of the network defined neighbourhood around the home was significantly associated with walking at 800m, 1200m and 1600m. Within these levels, the 400m neighbourhood level had the highest OR, 1.19, a relatively small effect size. In relation to destinations, walkability of the Euclidean defined neighbourhoods was significantly associated with walking up to 10 minutes at 1200m only. In contrast, however, there was no association between walkability (defined as BWI) and the network defined neighbourhood around destinations at any spatial level. Conversely, the walkability of routes showed significant positive associations with walking up to10 minutes for both the 50m and 100m buffers (Table 21).

Comparing between the network and Euclidean buffers around the home address, OR was highest for the network buffer at 800m, OR1.19 vs. OR1.16 for the Euclidean buffer. However, only the Euclidean buffer was associated too with the destination address at 1200m, with OR1.16.

After adjusting for demographic covariates in model 2, (Table 22), walkability around the home, based on the Euclidean buffer, remained significantly associated at 1200m only, and

800m for the network buffer around the home. In relation to walkability around the destinations, 1200m Euclidean buffer remained significantly positively associated with walking up to 10 minutes, whereas there was no association for the network buffers across any spatial scale. However, a strong association remained for the walkability of the built environment and walking up to 10 minutes along the route, OR1.26, at 50m and OR1.27 at 100m buffers (Table 23).

In model 3, after adjusting for employment and area deprivation, (Table 24), no associations between the BWI and walking up to 10 minutes was found for neighbourhoods around the home or destination addresses, for both Euclidean and network buffers across all spatial levels. However, the walkability of the route between home and destination remained significantly positively associated with time spent walking for both the 50m and 100m buffers. At the 50m and 100m buffers along the route, a unit increase in the BWI was associated with an estimated 22% and 24 %, respectively, increase in the odds of walking up to 10 minutes from home to destination environments (Table 25).

While there was no association between the BWI at either the home or destination environments in the fully adjusted models, significant associations were found along the routes. This finding indicates that further research into the route environment is required, rather than focusing solely on the residential home environment. Walkability along the routes from home to any destination can positively influence short walking trips.

Enhanced Walk Index

In model 1, (Table 20), the EWI (comprised of measures of land use mix, dwelling density, street connectivity, slope, footpaths and tracks, and street lights) around home addresses, was significantly positively associated with walking up to 10 minutes, with Euclidean buffers of 400m, 800m and 1200m. In addition, the ORs are highest at 400m and decreased as the spatial levels increased indicating that the walkability of 400m neighbourhoods predicts higher odds of time spent walking. The walkability (EWI) of the environment around home addresses, based on the network buffer, was also positively and significantly associated with walking up to 10 minutes across all spatial levels, (400m, 800m, 1200m, and 1600m). The ORs were highest for the 400m and 800m neighbourhood levels, OR1.21, and OR1.21. In relation to walkability around destinations, the Euclidean based neighbourhoods at 400m, 800m and 1200m were significantly positively associated with walking up to 10 minutes, similar to the home neighbourhoods, with relatively small effect sizes. In contrast, the walkability of only the 400m and 800m network defined neighbourhoods around the destinations were significantly positively associated with walking up to 10 minutes. In comparison to Euclidean buffers around the destinations, the OR at 400m was higher with the network buffers, where an increase in the walkability of the built environment was associated with 23% increased odds of walking up to 10 minutes. Regarding the routes between home and destinations, walkability was significantly associated with walking up to 10 minutes for both the 50m and 100m buffer (Table 21).

After adjusting for age, sex and ethnicity, (Table 22), the EWI remained significantly associated with walking up to 10 minutes around the home addresses, based on the Euclidean buffer, at 400m and 800m only. In addition, the walkability around the home, based on the network buffers, remained significantly positively associated across all levels. Walkability (EWI) around the destination addresses (Euclidean buffer) remained significantly associated with walking up to 10 minutes at 400m, 800m and 1200m and also reached significance at 1600m. In comparison, walkability of the network defined neighbourhood remained associated only at the 400m level. However, the walkability of the route between home and destination remained significantly associated with walking up to 10 minutes for both the 50m and 100m buffers (Table 23).

In the fully adjusted model (Table 24), after additionally controlling for employment and area deprivation, significant positive associations remained between walking up to 10 minutes and only the 400m Euclidean based neighbourhoods around home addresses, (OR1.28). In the network defined neighbourhoods around homes, the EWI remained significant and positively associated with time spent walking at both the 400m and 800m buffers (OR1.23 and OR1.22, respectively). ORs were marginally higher for the Euclidean buffers around the home. In relation to walkability around the destination environments, significant positive associations were found at the 400m Euclidean buffers only (OR1.19), however, there was no relationship found for the network buffers. In contrast, significant positive associations remained between the walkability along the route and up to 10 minutes spent walking, after adjusting for potential confounders (Table 25). A unit increase in the walkability, based on the EWI, along the route between home and destination environments was associated with an estimated 24% increase in the odds of walking up to 10 minutes, for both the 50m and 100m buffers.

Comparing results between the BWIs and the EWIs around the home, destination and route environments, the EWIs were found to be associated with all three environments (with the exception of only the network buffer around destinations) and walking up to 10 minutes. However, both the BWI and EWI along the route between home and destination predicted an increased likelihood of walking up to 10 minutes, with similar ORs.

There are a number of important findings arising from this analysis. The EWI for both the home and destination environments (excluding the network buffers around destinations) was significantly positively associated with short walking trips in neighbourhoods of 400m or 800m. This indicates that the EWI could be a useful neighbourhood measure for capturing time spent walking from the home to any destination environment. In addition, both the BWI and EWI were significantly and positively associated with time spent walking along the route, indicating the potential importance of the route environment in encouraging active travel behaviours.

Neighbourhood Destination Accessibility Index

The results of model 1, (Table 20), show strong and significantly positive associations between the density of destinations around home addresses, (Euclidean buffer), and walking up to 10 minutes at 800m, 1200m and 1600m. For example, the 1200m shows the strongest associations, where a unit increase in destination accessibility around homes was associated with an 80% increased odds of walking up to 10 minutes. In contrast, destination accessibility at the 1200m and 1600m network buffers around the home was significantly positively associated with walking for 10 minutes. Similar to the Euclidean buffer, the 1200m spatial level had the highest OR. In relation to the density of destinations around destination addresses, the NDAI was significantly positively associated at all neighbourhood levels. In addition, the 800m spatial level had the highest ORs, where a unit increase in destination accessibility around destinations was associated with a 66% increase in walking up to 10 minutes. However, remarkably, there was no association between destination accessibility and the network defined neighbourhoods, across all spatial levels, and time spent walking. (Table 20). In relation to destination accessibility along the route between home and destination, there was a significant positive association with walking up to 10 minutes at both 50m and 100m. The effect sizes were strong, with ORs ranging from OR1.62 to OR1.60 (Table 21).

After adjusting for age, sex and ethnicity, model 2, (Table 22), the NDAI did not remain associated with walking up to 10 minutes for the Euclidean buffer around the home address at 400m or 800m, however it did remain significant at 1200m and became significantly associated at 1600m, with the highest OR, 1.94. In relation to the network buffers around the home address, the NDAI was significantly associated at only the 1600m, but the effect size was strong, OR2.23. Destination accessibility remained significantly associated with walking up to 10 minutes at 800m, 1200m and 1600m Euclidean buffers around destination address. The highest OR was at 1200m, where a unit increase in destination accessibility was associated with a 93% increased odds in walking up to 10 minutes. Similar to model 1, there was no association between the NDAI and network buffers around destinations across any spatial level. Regarding destination accessibility along the route, the NDAI remained significantly associated with walking up to 10 minutes for the 50m buffer only, with ORs decreasing slightly from OR1.62 to OR1.57 (Table 23).

In the fully adjusted model, after including employment and area deprivation as potential confounders, (Table 24) no association remained between the home environments, based on the Euclidean buffer and time spent walking across all spatial levels. In addition, no associations were found for the network based buffer around the home addresses, the 1600m did not retain any statistical association, indicating potential negative confounding of employment and area deprivation. Moreover, in relation to the destination environments, the Euclidean based neighbourhoods remained significantly associated with walking up to 10 minutes at 1200m only. However, the OR was strong, where a unit increase in destination accessibility around destination addresses was associated with an estimated 76% increase in the odds of walking for up to 10 minutes. In contrast, there was no association between short walking trips and the NDAI around destination addresses, based on the network buffer at any spatial scale. Additionally, destination accessibility along the route did not remain associated with time spent walking, for either the 50m or 100m buffers (Table 25).

These results indicate that a number of demographic, socio-economic and area deprivation covariates can influence the relationship between the NDAI and short walking trips.

5.4.4 Associations of individual attributes and composite indices of the built environment and total time spent walking

This section reports the results of associations of the fully adjusted model, (model 3, Table 26 and Table 27) between the individual attributes and composite indices, (BWIs, EWIs and NDAIs) of the built environment and total time spent walking. GLM regression models based on the gamma distribution with log link were used to test associations between the continuous outcome, total duration (in minutes) walking to a destination and elements of the built environment. In addition, the coefficients were exponentiated in order to report the percent change in time spent walking per unit increase in attributes or indices of the built environment. The following research questions guide the analyses:

A) Are individual elements of the built environment and indices of walkability (BWIs and EWIs) and neighbourhood destination accessibility (NDAI) associated with total time spent walking from home to any destination?

B) Do results vary depending on 1) buffer delineation around the home, destination or along the route and 2) spatial scale?

Individual built environment measures

Moderate to strong positive associations were found, in the fully adjusted model, (model 3, Table 26), for total time spent walking and land use mix around the home environment based on the Euclidean buffer, at 1600m, 2000m and 2400m. Of the three spatial levels, land use mix at 2000m had the highest percentage change, where every unit increase in land use mix was associated with an estimated 63% increase in time spent walking from home to any destination. For the network buffers around the home address, land use mix was significantly and positively associated with total time spent walking at 2400m level only, (OR1.22). In contrast, density of land use mix around the destination environments based on the Euclidean buffers, was significantly positively associated with total time spent walking at the 800m and 1200m levels only, OR1.18 and OR1.19 respectively. In relation to the network buffers around destinations, similar to the home environment, there was a significant positive association only at the 2400m spatial level, OR1.21. However, there was no association between total time spent walking and density of land use mix along the route between home and destination environments (Table 27).

These results indicate there is much variation in associations between land use mix and total time spent walking depending on how the neighbourhood is delineated, whether Euclidean or network and also spatial scales are important. Strong associations existed between the Euclidean based neighbourhoods around home and destination environments and time spent walking at a number of spatial levels, indicating the importance of land use mix in predicting time spent walking. In comparison, the network based neighbourhoods, around both the home and destination addresses reached statistical significance at only one level, 2400m, potentially indicating that network buffers are not as useful in predicting associations between time spent walking and land use mix.

In the fully adjusted model, (Table 26 and Table 27), most of the other individual attributes had no associations with total time spent walking. There was no association between street connectivity, dwelling density, street lights, footpaths and tracks, and total time spent walking to any destination, for all three environments, home, destination and route, Euclidean or network, at any spatial scale.

However, low slope density around the home and destination environments based on the Euclidean buffers, was significant and negatively associated with total time spent walking at 2000m and 2400m buffers only. In addition, the percentage change was higher for the home rather than the destination environments, where low density of slope around the home was associated with an estimated 24% and 29% decrease in time spent walking at 2000m and 2400m, respectively. This result could reflect the topography of Wellington City, which is mountainous in residential areas, and slope has little impact on total time spent walking to destinations. In contrast, no association was found between low density of slope around network defined neighbourhoods for both the home and destination addresses, and along the route environment, at any spatial level, and total time spent walking.

Composite Indices of the built environment

After also adjusting for both demographic and socio-economic, model 3 (Table 26 and Table 27) was additionally adjusted for employment and area deprivation. There was no association between the BWI and total time spent walking around the home environments for both the Euclidean and network buffers at any spatial level. However, walkability of the built environment (BWI) around the destination addresses was significant and positively associated with total time spent walking at both the Euclidean, 400m only, and network defined neighbourhoods, 400m and 2000m only. Furthermore, a unit increase in the walkability of the environment around destinations was associated with an estimated 4% increase in time spent walking to any destination, for both the Euclidean buffers at 400m, and the network buffers at 400m and 2000m. However, no association was found between walkability along the route and total time spent walking (Table 27).

Furthermore, no association was found for either the EWI and NDAI and total time spent walking in any of the three neighbourhood environments, home, route and destination, both Euclidean and network, at any spatial scale.

These results indicate that the walkability, based on the BWI, of the destination environment, both Euclidean and network, is important for predicting total time spent walking from home to a destination.

Table 26. Separate GLM regression models based on the Gamma distribution with log link, fully adjusted for demographic, socio-economic and area deprivation, testing associations between individual and composite measures of the built environment and total time spent walking for neighbourhood buffers, Euclidean and network, around the home and destination addresses at 400m, 800m, 1200m and 1600m buffers. Odds ratios and confidence intervals (95%) are presented.

Total time spent walking	**Model 3 (fully adjusted for socio-demographic and deprivation)**											
	400m		**800m**		**1200m**		**1600m**		**2000m**		**2400m**	
Home address Euclidean buffer	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**
Land use mix	1.02	0.95-1.10	1.04	0.94-1.14	1.11	0.95-1.30	**1.38***	**1.06-1.79**	**1.63*****	**1.22-2.17**	**1.47****	**1.11-1.93**
Street connectivity	1.03	0.95-1.11	1.04	0.94-1.14	1.05	0.94-1.18	1.07	0.94-1.23	1.07	0.93-1.23	1.06	0.93-1.21
Dwelling density	1.03	0.95-1.11	1.03	0.94-1.14	1.06	0.94-1.20	1.09	0.95-1.25	1.07	0.94-1.22	1.05	0.93-1.19
Slope	0.99	0.92-1.06	1.02	0.90-1.15	1.01	0.85-1.20	0.93	0.75-1.14	**0.76***	**0.59-0.99**	**0.71***	**0.54-0.94**
Street lights	1.03	0.95-1.12	1.03	0.95-1.12	1.04	0.94-1.15	1.05	0.95-1.17	1.05	0.95-1.16	1.04	0.94-1.15
Footpaths and tracks	1.05	0.88-1.24	1.04	0.88-1.21	1.05	0.89-1.23	1.08	0.91-1.28	1.10	0.92-1.32	1.07	0.91-1.25
BWI	1.04	0.99-1.08	1.03	0.99-1.08	1.04	0.99-1.08	1.04	0.99-1.09	1.03	0.99-1.08	1.01	0.97-1.05
EWI	1.00	0.96-1.05	1.02	0.98-1.07	1.03	0.99-1.08	1.03	0.99-1.07	1.01	0.97-1.06	1.02	0.98-1.06
NDAI	1.03	0.91-1.16	1.06	0.91-1.21	1.06	0.91-1.22	1.06	0.92-1.22	1.05	0.92-1.18	1.04	0.93-1.16

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 26. continued.

Total time spent walking	Model 3 (fully adjusted for socio-demographic and deprivation) 400m		800m		1200m		1600m		2000m		2400m	
Home address network buffer	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**
Land use mix	1.02	0.96-1.09	1.03	0.96-1.11	1.06	0.96-1.17	1.09	0.95-1.25	1.13	0.96-1.33	**1.22***	**1.01-1.47**
Street connectivity	1.03	0.95-1.11	1.04	0.95-1.14	1.05	0.94-1.18	1.08	0.94-1.25	1.08	0.91-1.27	1.10	0.90-1.34
Dwelling density	1.02	0.94-1.11	1.02	0.94-1.12	1.05	0.94-1.16	1.08	0.95-1.23	1.08	0.94-1.24	1.10	0.94-1.28
Slope	0.97	0.91-1.03	0.97	0.89-1.06	0.99	0.91-1.09	1.01	0.91-1.12	0.99	0.88-1.11	0.95	0.83-1.08
Street lights	1.02	0.95-1.11	1.03	0.95-1.12	1.04	0.95-1.14	1.06	0.95-1.18	1.05	0.93-1.18	1.05	0.93-1.20
Footpaths and tracks	1.03	0.84-1.24	1.04	0.84-1.27	1.04	0.79-1.36	1.07	0.78-1.44	1.08	0.80-1.45	1.12	0.79-1.60
BWI	1.04	0.99-1.08	1.02	0.97-1.06	1.03	0.99-1.08	1.04	0.99-1.09	1.03	0.99-1.08	1.03	0.99-1.08
EWI	1.00	0.96-1.05	1.00	0.96-1.05	1.01	0.97-1.06	1.03	0.99-1.08	1.02	0.97-1.06	1.02	0.98-1.06
NDAI	1.02	0.91-1.13	1.06	0.93-1.21	1.08	0.91-1.26	1.08	0.90-1.28	1.07	0.89-1.26	1.10	0.91-1.32

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 26. continued.

Total time spent walking	Model 3 (fully adjusted for socio-demographic and deprivation) 400m		800m		1200m		1600m		2000m		2400m	
Any destination address Euclidean buffer	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**
Land use mix	1.07	0.99-1.16	**1.18****	**1.05-1.33**	**1.19***	**1.01-1.41**	1.10	0.88-1.37	1.08	0.84-1.39	1.07	0.82-1.38
Street connectivity	0.98	0.91-1.05	0.97	0.89-1.05	0.97	0.88-1.07	1.01	0.90-1.12	1.04	0.92-1.16	1.01	0.90-1.15
Dwelling density	0.96	0.9-1.02	0.94	0.87-1.01	0.96	0.87-1.05	1.03	0.92-1.15	1.04	0.92-1.18	1.03	0.90-1.17
Slope	0.98	0.93-1.04	1.02	0.94-1.11	1.07	0.93-1.23	0.98	0.80-1.20	**0.80***	**0.64-1.00**	**0.76***	**0.59-0.98**
Street lights	0.97	0.90-1.03	0.97	0.90-1.04	0.99	0.91-1.07	1.02	0.94-1.12	1.05	0.95-1.15	1.04	0.94-1.15
Footpaths and tracks	0.92	0.81-1.04	0.95	0.83-1.07	0.95	0.82-1.09	0.98	0.84-1.14	1.01	0.87-1.18	1.00	0.86-1.16
BWI	**1.04***	**1.00-1.08**	0.99	0.95-1.03	0.99	0.95-1.03	1.00	0.96-1.05	1.00	0.95-1.04	0.98	0.94-1.03
EWI	0.98	0.94-1.02	0.99	0.95-1.03	0.98	0.94-1.03	1.00	0.95-1.04	0.99	0.95-1.04	0.99	0.94-1.04
NDAI	0.99	0.89-1.09	0.99	0.89-1.10	1.00	0.89-1.11	1.01	0.89-1.13	1.00	0.89-1.12	0.99	0.89-1.11

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 26. continued.

Total time spent walking	Model 3 (fully adjusted for socio-demographic and deprivation)											
	400m		800m		1200m		1600m		2000m		2400m	
Any Destination address network buffer	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**	**Percent change**	**CI (95%)**
Land use mix	1.06	0.99-1.14	1.08	0.98-1.18	1.08	0.97-1.19	1.07	0.94-1.22	1.12	0.95-1.32	**1.21***	**1.00-1.47**
Street connectivity	0.99	0.92-1.07	1.01	0.92-1.04	1.04	0.93-1.15	1.06	0.94-1.21	1.09	0.94-1.26	1.11	0.93-1.33
Dwelling density	0.97	0.91-1.04	0.96	0.89-1.04	0.98	0.89-1.08	1.01	0.90-1.13	1.05	0.91-1.20	1.05	0.90-1.23
Slope	0.97	0.92-1.01	0.99	0.94-1.05	1.02	0.94-1.10	1.02	0.93-1.12	1.04	0.92-1.17	0.97	0.85-1.11
Street lights	0.99	0.92-1.06	1.00	0.92-1.08	1.02	0.93-1.12	1.04	0.94-1.15	1.05	0.94-1.17	1.06	0.94-1.20
Footpaths and tracks	0.93	0.80-1.07	0.95	0.79-1.12	0.94	0.75-1.16	0.98	0.76-1.25	1.01	0.77-1.30	1.01	0.74-1.34
BWI	**1.04***	**1.00-1.08**	1.00	0.96-1.05	1.01	0.97-1.06	1.03	0.98-1.07	**1.04***	**1.00-1.09**	1.04	1.00-1.08
EWI	0.98	0.93-1.02	1.00	0.96-1.04	1.03	0.98-1.07	1.02	0.98-1.07	1.02	0.97-1.07	1.02	0.98-1.07
NDAI	1.01	0.92-1.10	1.01	0.92-1.11	1.06	0.94-1.18	1.08	0.94-1.25	1.09	0.93-1.28	1.11	0.93-1.32

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

Table 27. Separate, GLM regression models based on the Gamma distribution with log link, adjusted for age, sex and ethnicity, employment and area deprivation, of associations between individual and composite measures of the built environment and total time spent walking along the route from home to destination at 50m and 100m buffers. Odds ratios and confidence intervals (95%) are presented.

Total time spent walking	Route buffer Model 3 (fully adjusted for socio-demographic and deprivation)			
	50m		100m	
	Percent change	CI (95%)	Percent change	CI (95%)
Land use mix	1.01	0.93-1.09	1.01	0.93-1.09
Street connectivity	1.01	0.94-1.08	1.01	0.94-1.08
Dwelling density	1.00	0.93-1.07	1.00	0.93-1.07
Slope	1.00	0.95-1.05	1.00	0.95-1.05
Street lights	1.01	0.93-1.09	1.01	0.93-1.09
Footpaths and tracks	0.96	0.80-1.13	0.97	0.81-1.13
BWI	1.00	0.96-1.05	1.00	0.95-1.05
EWI	1.00	0.95-1.04	1.00	0.96-1.04
NDAI	1.02	0.92-1.12	1.02	0.93-1.12

Values highlighted in bold indicate statistically significant associations, * =p<0.05, ** =p<0.01 and *** =p<0.001.

5.5 Summary of findings

This chapter has explored associations between individual and composite measures of the built environment and time spent walking. The sample size of individual participants that walked directly from their home environment to any destination for both outcome variables was relatively small, (n=55 for those that walked up to 10 minutes and n=133, total time spent walking). Therefore results should be interpreted with some caution. To aid with interpretation, summary tables of associations for each individual and composite measure and time spent walking are provided (Tables 28 and 29).

Table 28. Summary of associations of individual and composite measures of the built environment and walking up to 10 minutes, based on the fully adjusted model results.

Built environment measures	Home Euclidean	Home network	Destination Euclidean	Destination network	Route
High land use mix density	✗	✗	✓ – (800m)	✗	✗
High street connectivity density	✗	✗	✗	✗	✗
High dwelling density	✗	✓+ (800m)	✓ + (400m, 800m, 1200m)	✓ + (400m,800m)	✗
Low slope density	✓ + (1600m)	✓ + (400m)	✗	✗	✗
High street lights density	✗	✗	✓ + (400m, 800m)	✗	✗
High footpath and track density	✗	✗	✓ + (400m, 800m, 1200m)	✗	✓ + (50m,100m)
High BWI density	✗	✗	✗	✗	✓ + (50m,100m)
High EWI density	✓ + (400m)	✓ + (400m,800m)	✓ + (400m)	✗	✓ + (50m,100m)
High NDAI density	✗	✗	✓ + (1200m)	✗	✗

The symbol✓ denotes a statistically significant association, + indicates whether the association is positive and - indicates a negative association. The symbol ✗ indicates no association was found between the built environment measure and up to 10 minutes spent walking.

Table 29. Summary of associations of individual and composite measures of the built environment and total time spent walking, based on the fully adjusted model results.

Built environment measures	Home Euclidean	Home network	Destination Euclidean	Destination network	Route
High land use mix density	✓ + (1600m, 2000m, 1400m)	✓ + (2400m)	✓ + (800m, 1200m)	✓ + (2400m)	✗
High street connectivity density	✗	✗	✓ + (400m)	✗	✗
High dwelling density	✗	✗	✗	✗	✗
Low slope density	✓ – (2000m, 2400m)	✗	✓ – (2000m, 2400m)	✗	✗
High street lights density	✗	✗	✗	✗	✗
High footpath and track density	✗	✗	✗	✗	✗
High BWI density	✗	✗	✓ + (400m)	✓ + (400m,2000m)	✗
High EWI density	✗	✗	✗	✗	✗
High NDAI density	✗	✗	✗	✗	✗

The symbol ✓ denotes a statistically significant association, + indicates whether the association is positive and - indicates a negative association. The symbol ✗ indicates no association was found between the built environment measure and total time spent walking.

5.5.1 Relationships between individual attributes of the built environment and time spent walking, including up to 10 minutes and total time

Land use mix

Focusing on the results of the fully adjusted models, (model 3, Table 24 - Table 27), there was no association between land use mix and Euclidean or network based neighbourhoods around the home environment. In contrast, density of land use mix in the Euclidean based neighbourhood around destinations (800m) was significantly negatively associated with walking up to 10 minutes. Whereas no association was found between the network based buffer around destinations and the environment along the route and walking up to 10 minutes. Comparing with the second outcome, total time spent walking to any destination, land use mix was significantly positively associated with time spent walking in both the home and destination environments at both the Euclidean and network buffers and various spatial levels. Similar to walking up to 10 minutes, no association was found between total time spent walking and land use mix along the route. These results reveal a number of critical findings. Firstly, that there is much variation between land use mix and total time spent walking, depending on the neighbourhood delineation and spatial scale utilised. The Euclidean based neighbourhoods had strong associations around both the home and destination environments at a number of spatial levels, in comparison to the network based neighbourhood with only one scale associated (2400m). These results suggest that the Euclidean buffer is better in predicting associations between total time walking and land use mix. Secondly, these findings indicate that the land use mix measure, in both the home and destination environments, is important in predicting longer duration of time spent walking to destinations rather than short trips up to 10 minutes.

Street connectivity

After adjusting for demographic, socio-economic and area deprivation potential confounders, (model 3, Table 24 - Table 27), significant positive associations were found between street connectivity and walking for up to 10 minutes in the destination environment at 400m based on Euclidean buffer. However, no association remained between street connectivity and total time spent walking to any destination in either the home, destination or route environments, both Euclidean and network, at any spatial scale. This finding is in contrast to previous research in New Zealand, which has found associations between self-reported total minutes walking for all purposes and street connectivity (Witten et al., 2012). However, not all research linking active travel and street connectivity has found significant associations, (Oakes et al., 2007). Indeed, similar to Oakes et al., (2007), this study's sampling design, including the size and the covariates controlled for in the analyses could have led to mitigating residual confounding.

Dwelling density

In the fully adjusted model, dwelling density was found to be associated with walking up to 10 minutes in the home neighbourhood, based on the network buffer only at 800m. In addition, dwelling density was significantly positively associated with walking up to 10 minutes in neighbourhoods around destinations for both Euclidean buffers at 400m, 800m and 1200m and network buffers at 400m and 800m only. In contrast, Witten et al., (2012) found positive associations between dwelling density (per meshblock) and total minutes spent walking, however, Mackenbach et al., (2016) found significant negative associations between total time spent walking and dwelling density in the meshblock around the home, (destination results not reported). Furthermore, significant positive associations existed between dwelling density along the route and walking up to 10 minutes. There was no association between total time spent walking and dwelling density in the fully adjusted model. The results of this analysis could indicate that dwelling density is an important factor in predicting short walking trips in the home and destination environments.

Slope

After adjusting for all covariates in the analyses, the density of low slope around the home environment based on the Euclidean buffer at 1600m only, was significantly positively associated with walking up to 10 minutes (OR2.26, CI 1.07-5.05). In addition, low slope density around the home environment based on the network buffer was significantly associated at 400m only. However, no association was found for the environments around the destinations and short walking trips, for both the Euclidean and network buffers at any spatial scale. Comparing results with the second outcome, total time spent walking, low slope density around the home and destination environments, based on the Euclidean buffers at 2000m and 2400m only, was significantly negatively associated with overall time spent walking. In addition, no association was found for slope around the destinations, based on the network buffers, at any spatial scale, and total time spent walking. For both outcomes, no association existed between slope along the route and time spent walking. These results indicate that slope (both low and high density) around the home and destination environments could be an important predictor for both short and overall time spent walking. Previous research in New Zealand by Witten et al., (2012) and Mackenbach et al., (2016) did not include slope in their analyses, even though neighbourhoods in Wellington City (a mountainous area) were investigated.

Street lights

In the final fully adjusted models (Table 24 - Table 27), there was no association between street light density around the home environment, both Euclidean and network, at any spatial level and up to 10 minutes spent walking. However, significant positive associations were found in the Euclidean based neighbourhoods around destinations at 400m and 800m only and short walking trips. After additionally adjusting for employment and area deprivation, no association remained between walking up to 10 minutes and the network buffer around destinations and the route environment. In addition, no associations were found between total time spent walking and street light density in all three environments, home, destination and route, for all buffers and spatial scales. These findings indicate firstly that assessing the destination environment rather than or in addition to the commonly assessed residential home neighbourhood can add further insight into features of the built environment that can affect physical activity behaviours. Secondly, identifying street light density as a measure to predict physical activity behaviours in neighbourhoods could be useful, especially if other commonly used attributes are unavailable.

Footpaths and tracks

After fully adjusting for demographic, socio-economic and area deprivation covariates in this analyses, (model 3, Table 24 - Table 27), there was no association between density of footpaths and tracks and walking up to 10 minutes in the home environment, for both the Euclidean and network buffers, across any scale. However, strong associations between footpath and track density existed in the Euclidean defined neighbourhoods around the destinations at 400m, 800m and 1200m. In addition, effect sizes were large, for example, the odds of walking up to 10 minutes increased by a factor of 3.91 per unit increase in footpath density (400m level). However, there was no association found between footpath density based on the network buffer around destinations or along the route and short walking trips. In addition, no associations were found between total time spent walking and footpath and track density for all three environments, home, destination and route, for all buffers and spatial scales. These findings are interesting and similar to those of the street lights measure; they indicate the potential utility of measuring footpath density in predicting walking behaviours and also the importance of measuring the destination environment for predicting associations with physical activity behaviours.

5.5.2 Relationships between composite indices of the built environment and time spent walking, including up to 10 minutes and total time.

Basic Walk Index (BWI)

Focusing on the results of the fully adjusted models, (Table 24 - Table 27), the BWI, comprised of measures of land use mix, street connectivity and dwelling density, was not associated with walking up to 10 minutes in either the home or destination environments, for both the Euclidean and network buffers, across all spatial scales. However, significant positive associations were found between the walkability of the route environment and walking up to 10 minutes. For both the 50m and 100m buffers, a unit increase in walkability of the route was associated with an estimated 22% and 24% increase in the odds of walking up to 10 minutes from home to any destination. This is a significant finding as little research exists on investigating the environment along the route and physical activity behaviours. In addition, this finding indicates that the walkability of the route environment is potentially more important for predicting short walking trips.

Similar to short walking trips, there was no association between the BWI and the home environment, both Euclidean and network, at any spatial scale, and longer walking trips, (total duration). However, walkability around the destinations was significantly positively associated with total time spent walking in both the Euclidean, 400m only, and network, 400m and 2000m, environments. In contrast to short walking trips, no association was found between walkability along the route and total time spent walking. In summary, only walkability along the route environment, as opposed to the home and destination environment, was important in predicting short walking trips. However, similar to previous findings on street lights and footpaths, the walkability of the environment around the destinations is an important predictor of longer walking trips.

Enhanced Walkability Index (EWI)

Results from the fully adjusted model, (Table 24 - Table 27), revealed significant positive associations between the EWI around the home environment, both Euclidean at 400m and network 400m and 800m buffers, and short walking trips. In addition, the walkability of the destination environment for the Euclidean buffer only, was significantly positively associated with walking up to 10 minutes at the 400m spatial scale. Furthermore, similar to the

BWI, the walkability along the route was positively associated with an increased likelihood in walking up to 10 minutes, for both the 50m and 100m buffers. In relation to total time spent walking, no association was found with the EWI for all three neighbourhoods, home, destination and route environments.

Findings arising from the analyses of both the BWI and EWI, reveal the potential utility in using these composite indices of walkability to measure associations with physical activity behaviours. Hence, these indices and their associations with active transport behaviours and health outcomes will be further investigated in Chapters 6 and 7.

Neighbourhood Destination Accessibility Index (NDAI)

After fully adjusting for demographic, socio-economic and area deprivation, (Table 24 - Table 27), no association remained between destination accessibility around the home environment, either Euclidean or network, and up to 10 minutes spent walking at any spatial scale. However, destination accessibility around the destination addresses, based on the Euclidean buffer at 1200m, was significantly positively associated with short walking trips (OR1.76). In contrast, no association was found for either the network defined neighbourhoods around destinations or along the route and walking trips up to 10 minutes. In relation to total time spent walking, no association was found for all three environments, home, destination and route, across any buffer or spatial scale. These results indicate that having a high density of destinations in close proximity to other destinations could potentially encourage short walking trips.

5.6 Conclusion

The exploratory analyses in this chapter has revealed that associations between multiple individual and composite indices of the built environment and time spent walking are sensitive to the choice of neighbourhood delineation, Euclidean or network, and spatial scale utilised. For example, depending on neighbourhood delineation and spatial scale, both walkability indices (BWI and EWI) were associated with short walking trips. Specifically, the walkability of the home, destination and route environments, based on the EWI, were associated with walking up to 10 minutes, while only the walkability of the destination and route environments, based on the BWI, were associated with short walking trips. In addition, associations were found between longer walking trips and walkability, based on the BWI only, around destination environments. The results indicate that along with the residential home environment, the destination and route environments are also important in predicting associations between time spent walking and measures of the built environment. Finally, testing associations separately for both the individual and composite indices and time spent walking revealed that results are sensitive to demographic, socio-economic and area deprivation variables.

The following two chapters (Chapters 6 and 7) provide results on the main methods of this thesis described in Chapter 3 and 4. These chapters investigate the relationships between the composite indices of the built environment (BWI, EWI, BI and NDAI) and active transport behaviours and health outcomes.

Chapter 6: Measuring Associations between Indices of the Built Environment and Active Transport

6.1 Introduction

Research investigating the built environment and active transport behaviours such as walking and cycling is increasing in quantity. Identifying associations between features of the built environment that promote or hinder walking and cycling to work are important for increasing active transport, physical activity and health outcomes. Encouraging active transport behaviours could help individuals achieve the recommended daily physical activity guidelines, while travelling to and from work. Accordingly, the New Zealand Transport Agency (NZTA) recognises the important role the built environment plays in encouraging or hindering active transport (Genter et al., 2008). There is a multitude of benefits associated with active transport, including, health, economic and reduced environmental impacts (Genter et al., 2008).

This chapter addresses the ninth objective of this thesis, which is to comprehensively test the validity and associations of each of the standard and novel indices, described in Chapter 4, and active transport behaviours using the 2013 New Zealand Census (henceforth referred to as the Census). The corresponding research questions are presented at the beginning of each section of results. A brief description of the data and variables utilised to test these associations between the built environment and active transport variables follows, then an a detailed overview of the statistical analyses is provided. The results of associations between the Basic Walk Indices (BWIs), the Enhanced Walk Indices (EWIs), the Bike Indices (BIs) and the Neighbourhood Destination Accessibility Indices (NDAIs) and walking and cycling to work are presented (sections 6.4.2 – 6.4.5) and a discussion of the main findings arising from this analyses is offered (section 6.5).

6.2 Methods

Study data

The Census was used to validate and test associations between indices of the built environment, and active transport behaviours in Wellington City. The Census is a nationwide survey completed every 5 years (except in 2011, due to the Christchurch earthquakes) and records the official counts of population and dwellings as well as demographic, employment, housing, ethnic, religious, and living conditions (Statistics New Zealand, 2014). The latest data available and utilised in this research is from the 2013 Census. Census data is publicly available at a number of geographic spatial levels, including meshblock, area unit, ward, territorial authority area, and regional council. This thesis research is interested in measuring neighbourhood level exposures and the meshblock area level is the most appropriate. It is the smallest geographic unit representing approximately 110 people (Statistics New Zealand, 2002). Meshblock data for Wellington city was sourced from the Statistics New Zealand website (Statistics New Zealand, 2014). The following sections describe the outcome variables of interest, the potential confounders and briefly the exposure variables (built environment indices) used in these analyses.

6.2.1. Main means of travelling to work

The meshblock counts of two outcome variables (walking and cycling to work) were used to test associations between active transport behaviours and indices of the built environment. The variables obtained from the Census were defined as: the main means of travel to work for the for the usually resident, employed, population aged 15 years and over, who either (1) walked or jogged or (2) cycled. These variables represent the individuals that decided to use active transport modes to get to work on Census day. Other commuters such as public transport users or drivers of private vehicles were not included as this analysis was primarily concerned with testing relationships between the built environment and active transport.

6.2.2. Area level covariates

Demographic and Socio-economic covariates

It is common practice to account for demographic covariates in analyses on the built environment and active transport, as they represent potential confounders. As the Census data is aggregated to meshblock level, it is not possible to obtain individual level data. Even though individual level data is preferred, however, using proportions as a proxy for individuals is the next best option available. Therefore, each of the demographic and socio-economic variables have been calculated as proportions of the total population at the meshblock level.

Age and Sex

The Census provides the count of the usually resident population by age groups in five categories. In order to reduce the number of age groups for meaningful interpretation, four age groups were created to represent individuals at different stages of their working life (Witten et al., 2012). The selected age groups consisted of 15-29, 30-44, 45-54 and 55-64 year olds in order to represent the working age population. In order to get the proportion of these age groups at the meshblock level, the total of each age group was divided by the total usually resident population. Similarly, the proportion of females to males was also calculated.

Ethnicity

The Census classifies six ethnic groups for the usually resident population, which includes, European, Māori, Pacific Peoples, Asian, MELAA (Middle Eastern, Latin American, and African) and Other (small ethnic groups). To simplify interpretation, the proportions of four ethnic groups were calculated, including the proportion of Māori, Pacific, Asian and European/Other.

Socio-economic covariates

Education

The Census collects information on the highest qualification obtained for the usually resident population aged 15 and over and in order to control for education as a potential confounder, the proxy, proportion of qualifications was also included in the analyses. Following Witten et al.,'s (2012) classification of qualification groups, five groups were created from the eleven groups classified in the Census. The proportion of each of these groups was calculated by dividing the total count for each qualification group by the total people that stated their qualification level. The groups derived, were the proportion of the meshblocks with: no high-school qualification, a high-school qualification, a post-high Scholl diploma/certificate, an undergraduate degree and a postgraduate degree.

Household Income

Household income can influence whether an individual can afford to buy a bicycle or car, which can be used to commute to work. Similarly if the household income cannot afford a vehicle to get to work, walking would be an alternative option. Therefore, the proportion of household income in each meshblock was calculated as a proxy for individual household income and potential confounder. The Census provides the total household income in groups for households in occupied private dwellings, these groups include: NZ$20,000 or less, NZ$20,000-30,000, NZ$30,000-50,000, NZ$50,000-70,000, NZ$70,000-100,000, greater than NZ$100,000. All but one group was included in the analyses, households with an income of NZ$20,000 or less as this was deemed less than a working income in a year and less likely to be working, when the focus of this research is on individuals that commute to work. The proportions of each household income group were calculated by dividing them by the total households that stated their income.

Number of vehicles per household

The number of vehicles a household has access to can influence whether or not individuals walk or cycle to work. The Census classifies four groups containing the number of vehicles for households in occupied private dwellings, they are: no vehicles, one vehicle, two vehicles and three or more vehicles. The proportion of each of these groups of vehicles per household was calculated as a proxy for individual car ownership and included as potential confounders in the analyses.

Deprivation

The New Zealand Deprivation Index (NZDep13) is an area level measure of deprivation and was utilised to control for potential confounding in the analyses. It is comprised of nine variables from the 2013 Census and includes the variables: access to the internet, equivalised household income, means tested benefits, employment, single parent families, qualifications, home ownership, access to a car and household overcrowding (Atkinson et al. 2014). The NZDep13 was classified into quintiles and was included as a measure of deprivation at the meshblock area unit.

It is important to note that even though qualifications and access to a car are included in the NZDep13 index, it was considered conceptually important to include the variables, qualifications and number of vehicles per household as separate variables in the models as confounding could occur due to the outcome variables used and the effects could be masked in the index.

6.2.3. Built environment exposure measures

The exposure measures in the analyses described in this chapter include indices of the built environment measuring walkability, bikeability and neighbourhood destination accessibility. The methods used to create these indices are described in depth in Chapter 3. Briefly, the Basic Walk Index (BWI) is made up of three components, measures of land use mix, dwelling density and street connectivity. Three methods were used to create the BWIs at three spatial levels, 800m, 1600m and 2400m representing neighbourhood areas within a walking distance of 10, 20 and 30 minutes, respectively. Method 1 consisted of the standard method with network buffers of 800m, 1600m and 2400m around population weighted centroids (PWCs) and is frequently used in the literature (Frank et al., 2005; Leslie et al., 2007; Mavoa et al., 2009). Method 2 consisted of a kernel density estimation (KDE) based method (with a vector component), where values were averaged to Euclidean buffers of 800m, 1600m and 2400m around PWCs. Finally, method 3 consisted of a KDE based method (with a vector component), where values were averaged to network buffers of 800m, 1600m and 2400m around PWCs. The Enhanced Walk Index (EWI) was created using six built environment components, including the same three measures that comprise the BWI, measures of land use mix, dwelling density, street connectivity and additionally measures of street lights, footpaths and tracks and slope (steepness) were included in the index. As the EWI is unique to this thesis, it was only possible to apply methods 2 and 3 and at the same spatial levels (800m, 1600m and 2400m).

Methods 2 and 3 were also used to create two Bike Indices (BIs) at three spatial levels; 800m, 1600m and 2400m. The BIs were created using six components, measures of land use mix, street connectivity, slope, street lights, bike racks and cycle lanes. A detailed description of data sources, methods and maps can be found in Chapter 3, section 3.6.2.

Additionally, two Neighbourhood Destination Accessibility Indices (NDAIs) were created using methods 2 and 3 at three spatial levels; 800m, 1600m and 2400m. The NDAIs were composed of measures from eight destination domains, health, transport, education, retail, other retail, greenspace, financial, and social cultural (Mavoa et al., 2008).

6.3 Statistical analyses

Descriptive statistics, including the mean and median, were calculated for the dependant variables, walking and cycling and for each of the indices of the built environment (BWIs, EWIs and the NDAIs). The following paragraphs describe the statistical methods applied to the active transport variables of interest.

An initial analysis of the active transport dependant variables, counts of individuals walking to work and cycling to work, revealed over-dispersion, and an excessive number of zeros (23% and 44% respectively). It is not uncommon for count variables to be positively skewed and have many zeros (Atkins et al., 2013). In addition, count models rarely meet distribution assumptions which are required for ordinary least squares regression. A method commonly used to address skewed data is to transform the data in order to achieve a normal distribution, however, an excess of zeros will not be smoothed out by a transformation (Atkins et al., 2013). Therefore, zero-inflated negative binomial regression (ZINB) models with robust standard errors were used to determine associations between indices of the built environment and active transport modes. These are appropriate regression models that can account for excess zeros and over-dispersion (Beaujean and Morgan, 2016). Further, ZINB regression models, while not common in the environment and health literature, have been applied in a number of relevant examples. Research focusing on the personal, social and environmental attributes of physical activity (Cerin et al., 2010), and on the built environment and walking for transport (Kamruzzaman et al., 2016) applied ZINB models. Additional research on physical activity and cycling behaviour has also applied this type of model (Downward and Rasciute, 2015).

Furthermore, it is important to note, that the dependant variables of interest obtained from the Census, contain excess zeros which do not necessarily represent zero participants. This is due to random rounding. Counts of individuals are randomly rounded to a base of three to ensure individual characteristics are not identifiable in meshblocks with small numbers. The excessive zeros could represent zero, one or two individuals that walked or cycled to work (Statistics New Zealand, (2015d). For this reason, zeros cannot be removed or ignored from the analyses as they potentially represent real walkers or cyclists, who walked or cycled to work on Census day.

The ZINB regression model generates two separate models to distinguish behaviours of individuals, who did or did not walk or cycle to work. First, a negative binomial (NB) model is estimated, to predict how frequently the behaviour (walking or cycling) occurred. Second, a logit model is estimated for the “zeros, not zeros” and predicts the non-occurrence of the behaviour (walking or cycling to work) (Beaujean and Morgan, 2016; Aitkins and Gallop, 2007). To help with clarification, the zeros in the data can potentially have two meanings, they can represent participants or people who generally do walk to work but, for some reason did not walk on census day; and secondly, the zeros can also represent people who generally never walk to work, referred to here as non-participants. Both models produce two groups of coefficients, the NB regression coefficients predict how frequently the behaviour (walking or cycling) occurred, and the logistic regression coefficients predict if the behaviour (non-walking or non-cycling) never occurred (Beaujean and Morgan, 2016; UCLA: Statistical Consulting Group, 2016).

Bivariate and multivariate ZINB regression models were estimated for each method of the BWIs, the EWIs, the BIs and the NDAIs at each neighbourhood level (800m, 1600m and 2400m), and their associations with active transport modes. Table 30 presents an overview of the models applied and the potential confounder variables additionally included in models 2 and 3. Vuong tests were used to test whether a traditional NB model or a ZINB model was a better fit for the data (Cerin et al., 2010). The results for each of the multiple regressions showed that the ZINB models fitted the data significantly better than NB models.

The results of ZINB models are commonly interpreted by exponentiating the regression coefficients of both the NB and logit models (Beaujean and Morgan, 2016). Therefore, the coefficients were exponentiated and the 95% confidence intervals were also computed. Exponentiating the coefficients of the NB models (with log link) allows the percentage change in walking or cycling frequency per one unit increase in the exposure variables (indices of the built environment) to be estimated (Beaujean and Morgan, 2016; Foster et al., 2014). The exponentiated coefficients of the NB model can also be interpreted as factors, where a unit increase in the exposure variables is associated with an X times increase in the expected frequency of walking or cycling (when X is the value of the exponentiated coefficient). Exponentiating the coefficients of the logit model places the coefficients in an odds-ratio (OR) scale (Beaujean and Morgan, 2016). An example interpretation of the exponentiated coefficients for the ZINB model for walking to work is as follows: in the NB model, for every unit increase in the walkability of the built environment, walking frequency increases by 52% (percent change, exp(b)= 1.52). Another way of interpreting the same result is, a unit change in the walk index was associated with an estimated 1.52 times increase in the expected frequency of individuals walking to work. In the logit model, an OR of 0.80 can be interpreted as: a one unit increase in the walk index is associated with an estimated 20% decrease in the odds of being a non-participant in walking. In other words, individuals were less likely to be non-participants in walking to work as walkability of the built environment increased.

Given the diversity of methods applied in this research it is useful to determine which methods are more suitable than others for research on the built environment and active transport behaviours. Therefore, in order to determine superiority for each of the methods used to create the indices of the built environment, Akaike's information criterion (AIC) was applied. The AIC is a goodness-of-fit measure of the data which also penalises model complexity (Beaujean and Morgan, 2016). AIC values on their own are difficult to interpret, they are primarily used to develop comparisons between models. Models with the smallest AIC value are considered the best fit for a given dataset (Beaujean and Morgan, 2016). Finally, all analyses were completed in *R* (R Development Core Team, 2014), an open source software environment for statistical and graphical computing.

Table 30. Example table of multiple models applied to test for associations between outcome and exposure variables using Zero Inflated Negative Binomial regression models.

	Model 1 [a]: Unadjusted bivariate model	**Model 2 [b]: Adjusted for demographics**	**Model 3 [b]: Adjusted for socio-economic and area deprivation**
Outcome variables [a]	**Exposure variables**	**Exposure variables**	**Exposure variables**
Walking to work	- BWIs - EWIs - NDAIs (methods 3 & 4)	- BWIs - EWIs - NDAIs (methods 3 & 4)	- BWIs - EWIs - NDAIs (methods 3 & 4)
		Proportion of working age groups: -15-29 -45-54 -30-44 -55-64	**Proportion of working age groups:** -15-29 -45-54 -30-44 -55-64
		Proportion of ethnic groups: - Māori - Pacific - Asian - European/Other	**Proportion of ethnic groups:** - Māori - Pacific - Asian - European/Other
		Proportion of Females to Males	**Proportion of Females to Males**
			Proportion of Qualifications: - No high-school qualification - High-school qualification - Post-high school diploma/certificate - Undergraduate degree - Postgraduate degree
			Proportion of Household income: -NZ$20-30K -NZ$30-50K -NZ$50-70K -NZ$70-100K - > NZ$100K
			Proportion of vehicles/household: - No vehicles - One vehicle - Two vehicles - Three or more vehicles
			NZ Deprivation: - Quintile 1 - Quintile 2 - Quintile 3 - Quintile 4 - Quintile 5

[a] The second outcome variable, cycling to work was also tested for associations with the Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs), based on methods 2 and 3 at 800m, 1600m and 2400m spatial scales.
[b] Cycling to work was additionally controlled for potential confounders in models 2 and 3.

6.4 Results

The following section describes the summary statistics and then reports each of the unadjusted and adjusted results for each of the active transport modes and how they are associated with indices of the built environment for walking, cycling and neighbourhood destination accessibility.

6.4.1 Descriptive characteristics of covariates and associations with active transport modes

Summary statistics of the mean and standard deviations for each of the covariates are presented in Table 31. In addition, each of the covariates were tested for associations with the dependant variables of interest using the ZINB regression models. The age groups of 15-29 years old, and 45-54 years old were positively associated with walking to work, while the group of 30-44 years old was positively associated with cycling to work on census day. Regarding ethnicity, there was no significant association with walking to work. However, both Asian and European/Other ethnic groups were significantly associated with cycling to work.

Regarding education, the proportion of people with a high-school qualification, undergraduate degree and postgraduate degree, per meshblock, were significantly associated with walking to work. Similarly, high-school and post-high school qualifications were also significantly associated with cycling to work. The proportion of individuals having a household income between NZ$70-100K, per meshblock, is also significantly associated with walking to work. However, there are no similar associations between cycling to work and household income.

Regarding the number of vehicles per household, the meshblocks proportion of individuals with various numbers of vehicles per household was significantly associated with walking to work across all categories. In contrast, the meshblocks' proportion of individuals with access to only one vehicle per household was significantly associated with cycling to work. Amongst the deprivation quintiles, the largest proportion of participants (33.33%) belongs to Quintile 1 (least deprived), whereas the proportion of most deprived participants corresponds to 14.51% in Quintile 4, and 4.82% in Quintile 5, indicating that the sample has a relatively high percentage of least deprived groups per meshblock.

Table 31. Mean and standard deviations of meshblock proportions of sample characteristics and their associations with active and non-active transport modes commuting to work on census day in 2013.

Sample Characteristics of Census Meshblocks	Census (n= 1,988)		Walkers (n= 1,578)[a]	Cyclists (n=1,522)[b]
	Mean	**(Std)**	**P-value**	**P-value**
Age (years) [e]				
15-29	0.26	0.17	**<0.001**	0.11
30-44	0.24	0.08	0.39	**<0.001**
45-54	0.14	0.06	**<0.01**	0.41
55-64	0.10	0.05	0.41	0.11
Ethnicity				
Māori (missing n= 169)	0.08	0.07	0.07	0.06
Pacific (missing n= 170)	0.05	0.07	0.59	0.95
Asian (missing n= 171)	0.14	0.12	0.16	**<0.001**
European/Other (missing n= 171)	0.82	0.15	0.46	**<0.01**
Sex [f]				
Proportion of Females to Males	0.51	0.07	0.07	0.10
Qualification				
Proportions:				
No high school qualification (missing n= 312)	0.09	0.09	0.08	0.31
High school qualification (missing n= 318)	0.41	0.12	**<0.001**	**<0.001**
Post-high school diploma or trade certificate (missing n= 316)	0.09	0.05	0.80	**<0.001**
Undergraduate University degrees (missing n=260)	0.25	0.09	**<0.001**	0.06
Postgraduate University degree (missing n=318)	0.16	0.09	**<0.001**	0.14
Household Income (NZ$)				
Proportions:				
20,000-30,000 *(missing n=391)*	0.07	0.07	0.33	0.73
30,001-50,000 *(missing n=391)*	0.12	0.08	0.16	0.83
50,001-70,000 *(missing n=391)*	0.12	0.08	0.79	0.60
70,001-100,000 *(missing n=389)*	0.17	0.09	**<0.05**	0.66
>100,000 *(missing n=334)*	0.46	0.19	0.15	0.18

Table 31. continued.

	Census (n= 1,988) Mean	(Std)	Walkers (n= 1,578)[a] P-value	Cyclists (n=1,522)[b] P-value
Number of Household Vehicles				
Proportion:				
No vehicles *(missing n=292)*	0.14	0.16	**<0.001**	0.46
One vehicle *(missing n=281)*	0.48	0.14	**<0.001**	**<0.01**
Two vehicles *(missing n=293)*	0.30	0.15	**<0.001**	0.06
Three or more vehicles *(missing n=296)*	0.09	0.08	**<0.001**	0.16
New Zealand Deprivation Index 2013 [g]				
Quintile 1 (Less deprived) (%)	33.33	-	Ref.	Ref.
Quintile 2 (%)	25.98	-	**<0.001**	0.13
Quintile 3 (%)	21.36	-	**<0.001**	0.87
Quintile 4 (%)	14.51	-	**<0.001**	0.31
Quintile 5 (Most deprived) (%)	4.82	-	**<0.001**	0.28

Bold p-values indicate statistically significant associations (p<0.05).
[a] Missing data (n= 410) not included in the zero-inflated negative binomial models
[b] Missing data (n= 466) not included in zero-inflated negative binomial models
[c] Missing data (n= 446) not included in the negative binomial regression models
[d] Missing data (n= 467) not included in the negative binomial regression models
[e] Missing data in each age group, (n=288)
[f] Missing data in proportion of Females to males, (n=109)
[g] Missing data in New Zealand Deprivation Index (n= 81)

6.4.2 Walkability and walking to work

This section addresses the relations between walkability and walking to work, with specific research questions in mind to guide interpretation of the results, such as:

A) How are walkability and walking to work related to each other? Does the frequency of walking to work increase as the walkability of the built environment increases?

B) Does the probability of being a non-participant in walking to work decrease as the walkability of the built environment increases? And how do these associations vary depending on neighbourhood definition and scale, after controlling for potential confounding covariates?

The results from the ZINB models which test the associations between indices of walkability (BWIs and EWIs) are presented in the following section. The percent change in walking to work of the NB model is expected to be greater than 1, indicating an association with walkability. Also, the ORs of a non-participant walking to work are hypothesised to be less than 1, per unit increase in walkability, in the logit model.

Results for Model 1

Descriptive statistics of each of the BWIs and EWIs are presented in Table 32 and indicate a dissimilarity between the means and standard deviations of each of the methods. The results of the unadjusted bivariate model are also presented in Table 32 and show that both the BWIs and the EWIs are positively associated with walking to work (NB model) and reached statistical significance ($p<0.001$) with all methods. Furthermore, the odds of being a non-participant in walking to work were significantly ($p<0.001$) associated with decreases in all BWIs and EWIs across all spatial levels (logit model). After comparing the AIC values, (measure of goodness-of-fit), between each of the methods at the three neighbourhood levels, the BWI based on method 3, (network buffer), which had the lowest AIC values at 800m and 1600m, whereas the BWI based on the standard method 1, (network buffer) had the lowest AIC value at the 2400m spatial level.

When comparing each of the EWI methods, method 3 had the lowest AICs at all three neighbourhood levels, (800m, 1600m and 2400m), indicating model superiority. Comparing AICs between the BWIs and EWIs, the EWI based on method 3 was the only index to consistently achieve lower AIC values for the three spatial levels, indicating that the EWI based on method 3 is the best fit model to predict associations between walking to work and the odds of non-participants walking to work, at each neighbourhood level (800m, 1600m and 2400m).

Table 32. Unadjusted bivariate zero-inflated negative binomial model of associations between walking to work and the Basic Walk and Enhanced Walk Indices.

Walking to work			Percent change [a] in walking to work (95% CI) (negative binomial model)		Odds ratio [b] for being a non-participant in walking to work (95% CI) (logit model)		
	Model 1						
	Mean	**Std**	**Percent change**	**CI (95%)**	**OR**	**CI (95%)**	**AIC**
BWI Method 1							
800m	5.86	1.92	**1.36**	**1.32-1.39**	**0.68**	**0.62-0.75**	10033.04
1600m	5.94	1.94	**1.36**	**1.33-1.40**	**0.67**	**0.61-0.73**	9989.55
2400m	5.99	1.99	**1.39**	**1.36-1.42**	**0.64**	**0.59-0.70**	9817.78
BWI Method 2							
800m	7.45	1.53	**1.54**	**1.49-1.59**	**0.69**	**0.63-0.76**	9967.82
1600m	6.66	2.01	**1.44**	**1.41-1.48**	**0.78**	**0.73-0.84**	9862.90
2400m	6.04	2.17	**1.39**	**1.36-1.42**	**0.82**	**0.76-0.87**	9916.16
BWI Method 3							
800m	8.05	1.15	**1.88**	**1.79-1.97**	**0.48**	**0.41-0.57**	9812.76
1600m	7.83	1.22	**1.89**	**1.80-1.98**	**0.58**	**0.50-0.66**	9800.28
2400m	7.50	1.50	**1.64**	**1.58-1.69**	**0.72**	**0.65-0.79**	9845.36
EWI Method 2							
800m	7.04	1.26	**1.68**	**1.61-1.75**	**0.65**	**0.58-0.73**	9973.77
1600m	6.30	1.74	**1.54**	**1.49-1.59**	**0.76**	**0.70-0.83**	9881.75
2400m	5.71	1.98	**1.46**	**1.42-1.50**	**0.80**	**0.74-0.86**	9886.73
EWI Method 3							
800m	7.52	0.99	**2.16**	**2.05-2.28**	**0.42**	**0.34-0.50**	9718.13
1600m	7.37	0.95	**2.26**	**2.13-2.39**	**0.46**	**0.38-0.55**	9769.97
2400m	7.12	1.08	**2.06**	**1.95-2.16**	**0.57**	**0.50-0.66**	9791.90

Values highlighted in bold indicate statistically significant associations (p<0.001) and shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in walking to work per unit increase in neighbourhood walkability.
[b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in walking to work associated with a unit increase in neighbourhood walkability.

Results for Model 2

Model 2 was adjusted for proxy measures of age, sex and ethnicity, which included, the proportion of working age groups (15-29, 30-44, 45-54 and 55-64 year olds), the proportion of females to males and the proportion of ethnic groups (Māori, Pacific, Asian and European/Other) in each meshblock in Wellington City.

Table 33 shows significant (p. <0.001) positive associations between the BWIs, the EWIs, and walking to work after adjusting for potential confounders. Overall, the effect sizes decreased after adjusting for age, sex and ethnicity, indicating possible confounding. Similar to results from model 1, the percent change in walking to work was positive and significant across all spatial levels and proportional to a unit increase in the walkability of the built environment, irrespective of method used. The odds of being a non-participant in walking to work (logit model) decreased as the walkability of the built environment increased, for all methods and was statistically significant across all three spatial levels. Also, the AIC values across all methods showed improved performance and decreased after adjusting for age, sex and ethnicity.

Comparing the various the BWI methods, the BWI method 3 achieved the lowest AIC values at each neighbourhood level. At the 800m level, walking frequency (NB model) increased by 58% in comparison to 53% at 1600m, and 41% at 2400m for every unit increase in walkability (based on BWI method 3). In the logit model, at the 800m level, a one unit increase in walkability was associated with an estimated 49% decrease in the odds of being a non-participant in walking, and this was further reduced at 1600m, (38%), and 2400m (24%). These results indicate that the BWI based on method 3 at 800m neighbourhood level has the strongest associations with the outcome walking to work after adjusting for age, sex, and ethnicity. This suggests that providing walkable environments, (based on the network buffer), within a 10 minute walk could encourage active transport behaviours.

Comparing between the EWI methods, the EWI based on method 3 had much lower AIC values. In order to determine which type of index and method were most appropriate for measuring associations between walking to work and walkability, the AIC values across all BWIs and EWIs were compared. The EWI based on method 3 in comparison to all other methods was the best fit model, with lower AIC values across each neighbourhood level. This finding indicates that measuring additional features of the built environment such as density of street lights, slope, footpaths and tracks, and including them in the EWI have stronger statistical associations with walking to work.

Table 33. Zero-inflated negative binomial model of associations between walking to work and the Basic Walk Indices and Enhanced Walk Indices, adjusted for proxies of age, ethnicity and sex.

Walking to work	Percent change[a] of walking to work (95% CI) (negative binomial model)		Odds ratio [b] for being a non-participant in walking to work (95% CI) (logit model)		
	Model 2				
	Percent change	CI (95%)	OR	CI (95%)	AIC
BWI Method 1					
800m	**1.21**	**1.18-1.24**	**0.69**	**0.63-0.77**	9097.60
1600m	**1.22**	**1.19-1.25**	**0.70**	**0.63-0.77**	9077.14
2400m	**1.23**	**1.20-1.26**	**0.67**	**0.61-0.73**	9010.88
BWI Method 2					
800m	**1.31**	**1.27-1.36**	**0.70**	**0.63-0.77**	9055.35
1600m	**1.25**	**1.22-1.28**	**0.84**	**0.78-0.91**	9059.53
2400m	**1.21**	**1.18-1.23**	**0.87**	**0.81-0.94**	9093.78
BWI Method 3					
800m	**1.58**	**1.51-1.65**	**0.51**	**0.43-0.61**	8896.87
1600m	**1.53**	**1.46-1.60**	**0.62**	**0.54-0.71**	8960.73
2400m	**1.41**	**1.36-1.45**	**0.76**	**0.68-0.84**	8957.14
EWI Method 2					
800m	**1.40**	**1.35-1.46**	**0.64**	**0.57-0.72**	9041.35
1600m	**1.31**	**1.27-1.35**	**0.81**	**0.74-0.88**	9036.77
2400m	**1.26**	**1.23-1.29**	**0.84**	**0.78-0.91**	9034.65
EWI Method 3					
800m	**1.73**	**1.65-1.81**	**0.40**	**0.32-0.49**	8810.10
1600m	**1.77**	**1.68-1.87**	**0.47**	**0.39-0.57**	8872.20
2400m	**1.65**	**1.57-1.73**	**0.61**	**0.52-0.70**	8891.16

Values highlighted in bold indicate statistically significant associations ($p<0.001$) and shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in walking to work per unit increase in neighbourhood walkability. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in walking to work associated with a unit increase in neighbourhood walkability.

Results for Model 3

Model 3 was additionally adjusted for proxy measures of education, household income, household access to a car and a measure of neighbourhood deprivation. These variables were, the proportion of individuals with or without qualifications (no high school qualification, high school qualification, post-high school diploma or certificate, undergraduate degree and postgraduate degree); the proportion of household income (NZ$20-30K, NZ$30-50K, NZ$50-70K, NZ$70-100K and greater than NZ$100K); the proportion of household vehicles (no vehicles, one vehicle, two vehicles, and three or more vehicles), and deprivation (classified into quintiles).

In the fully adjusted model, similar to results for model 1 and 2, each of the BWIs and EWIs at each neighbourhood level was significantly ($p<0.001$) positively associated with walking to work (the NB model, Table 34). After adjusting for the covariates, the effect sizes of the percent change decreased for all methods indicating potential mediating effects of the covariates. In addition, similar to models 1 and 2, the results were in the expected direction. In the logit model, a unit increase in walkability was associated with significant decrease in the odds of being a non-participant in walking with all methods and spatial levels, with the exception of BWI and EWI based on method 2 at 1600m and 2400m, where no association was found. In the examination of the combined results of the ZINB model, it is interesting to note that method 3, (network buffer) for both BWIs and EWI, maintained significant associations with walking to work after adjusting for demographic, socio-economic and deprivation. In contrast, the BWI and EWI based on method 2 (Euclidean buffer) was not associated with the odds of being a non-participant walking to work at 1600m and 2400m. Furthermore, AIC values, similar to model 2 results, were lowest for BWI and EWI based on method 3, (represented in shaded cells in Table 34). These findings indicate that the network buffer is potentially a more appropriate method to use when measuring associations between walkability and walking for transport.

Comparing the BWI with the EWI methods, the EWI based on method 3 had the lowest AIC values across each neighbourhood level, indicating it is the best fit model to test associations between walkability and walking to work. Contrasting the results of each neighbourhood level within the EWI, based on method 3, the 800m neighbourhood was associated with a 40% increase (NB model) in walking frequency for every unit change in this walk index, and a unit increase was associated with an estimated 39% decreased odds of being a non-participant in walking. In addition, the AIC values were lowest for the 800m neighbourhood level. These results indicate, first, that overall the EWI based on method 3 at each neighbourhood level is the best fit for predicting associations with walking to work, and second that the 800m neighbourhood level, while effect sizes are marginal, is more appropriate than the 1600m and 2400m levels.

Table 34. Zero-inflated negative binomial model of associations between walking to work and the Basic Walk (BWI) and Enhanced Walk Indices (EWI), additionally adjusted for proxies of education, household income, access to a car and area deprivation.

Walking to work	Percent change[a] in walking to work (95% CI) (negative binomial model)		Odds ratio [b] for being a non-participant in walking to work (95% CI) (logit model)		
Model 3					
	Percent change	CI (95%)	OR	CI (95%)	AIC
BWI Method 1					
800m	**1.11**	**1.09-1.14**	0.86*	0.76-0.97	8055.43
1600m	**1.13**	**1.10-1.15**	0.85**	0.76-0.96	8025.63
2400m	**1.13**	**1.10-1.15**	**0.77**	**0.69-0.86**	**7998.93**
BWI Method 2					
800m	**1.16**	**1.13-1.20**	0.86*	0.76-0.97	8052.56
1600m	**1.12**	**1.09-1.15**	0.97	0.89-1.06	8066.23
2400m	**1.10**	**1.08-1.12**	0.96	0.89-1.04	8058.37
BWI Method 3					
800m	**1.34**	**1.28-1.40**	**0.70**	**0.58-0.85**	**7952.17**
1600m	**1.27**	**1.21-1.33**	**0.76**	**0.65-0.89**	**8012.45**
2400m	**1.22**	**1.18-1.26**	0.86*	0.76-0.97	7997.30
EWI Method 2					
800m	**1.20**	**1.15-1.25**	0.82**	0.71-0.94	8055.22
1600m	**1.15**	**1.12-1.18**	0.92	0.83-1.02	8051.59
2400m	**1.14**	**1.11-1.16**	0.92	0.85-1.01	8018.15
EWI Method 3					
800m	**1.40**	**1.34-1.48**	**0.61**	**0.48-0.77**	**7948.42**
1600m	**1.40**	**1.33-1.48**	**0.66**	**0.53-0.81**	**7973.32**
2400m	**1.36**	**1.30-1.42**	0.75**	0.63-0.90	7956.73

Values highlighted in bold indicate statistically significant associations at p<0.001; * = significance associations at p<0.05 and **= significance at p<0.01. Shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in walking to work per unit increase in neighbourhood walkability. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in walking to work associated with a unit increase in neighbourhood walkability.

6.4.3 Neighbourhood destination accessibility and walking to work

Having destinations that are accessible in the neighbourhood could potentially encourage all types of walking, not just walking for transport. However, it could be argued that having a nice environment to walk through, such as stopping off at a café or walking through a park while on route to work could encourage rather than hinder walking to work. This section examines whether there is a relationship between neighbourhood destinations and walking to work, using the following research questions to guide the investigation:

A) Does the frequency of walking to work increase as the accessibility of neighbourhood destinations increases?

B) Are the odds of being a non-participant in walking to work inversely proportional to the accessibility of neighbourhood destinations? And how does this vary, depending on neighbourhood definition and scale after controlling for potential confounding covariates?

Results for Model 1

Descriptive statistics of the NDAI methods and the results for the unadjusted bivariate ZINB model are presented in Table 35. Both methods of measuring the NDAIs were significantly ($p<0.001$) positively associated with walking to work across all neighbourhood levels. Effect sizes were small but still in the expected direction (greater than 1), indicating that for every unit increase in accessibility to neighbourhood destinations, the frequency of walking to work also increases, ranging from 6%-8% across all NB models. Additionally, both methods at all spatial levels in the logit model, were significantly negatively associated with being a non-participant in walking to work, although the effect sizes were small. The NDAI based on method 2 had the lowest AIC value at the 800m level, whereas the NDAI based on method 3 had the lowest AIC values at 1600m and 2400m, indicating the best model fit.

Table 35. Unadjusted bivariate, zero-inflated negative binomial model of associations between walking to work and the Neighbourhood Destination Accessibility Indices.

Walking to work			**Percent change[a] in walking to work (95% CI) (negative binomial model)**		**Odds ratio [b] for being a non-participant in walking to work (95% CI) (logit model)**		
			Model 1				
	Mean	**Std**	**Percent change**	**CI (95%)**	**OR**	**CI (95%)**	**AIC**
NDAI Method 2							
800m	30.32	12.12	**1.06**	**1.06-1.07**	**0.91**	**0.89-0.92**	9482.40
1600m	27.60	12.12	**1.07**	**1.07-1.07**	**0.92**	**0.91-0.93**	9374.03
2400m	25.48	12.01	**1.06**	**1.06-1.07**	**0.93**	**0.92-0.94**	9787.52
NDAI Method 3							
800m	33.98	14.64	**1.05**	**1.05-1.05**	**0.93**	**0.91-0.94**	9619.25
1600m	33.74	11.45	**1.07**	**1.07-1.08**	**0.89**	**0.87-0.91**	9311.56
2400m	32.82	10.64	**1.08**	**1.08-1.09**	**0.89**	**0.87-0.91**	9197.82

Values highlighted in bold indicate statistically significant associations ($p<0.001$) and shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in walking to work per unit increase in neighbourhood destination accessibility. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in walking to work associated with a unit increase in neighbourhood destination accessibility.

Results for Model 2 and 3

After adjusting for proxies of age, ethnicity and sex, each of the NDAI methods remained statistically significant across all spatial levels ($p<0.001$) and were associated with walking to work (NB model, Table 36). The addition of covariates reduced the effect sizes but the association remained statistically significant. In the logit model, both methods at each neighbourhood level remained significantly associated with the odds of being a non-participant in walking to work in the expected direction (less than 1). The effect sizes of the results of model 1 were small and were further decreased in model 2 after including covariates, indicating possible confounding. Similar to the results for model 1, the NDAI based on method 2 had the lowest AIC values at 800m, and the NDAI based on method 3 had the lowest AIC values at 1600m and 2400m. This suggests that the Euclidean buffer (method 2) is potentially a useful method for measuring associations between short distances and destinations. Further, the network buffer (method 3) could be more suitable for measuring the relationship between longer commutes by foot and destination accessibility.

Finally, in the fully adjusted model, (model 3), which was adjusted for proxies of education, household income, car access, and neighbourhood deprivation, both methods of measuring the NDAI remained significantly associated ($p<0.001$) with walking to work (NB model), even though effect sizes were marginal. The odds of being a non-participant in walking to work significantly decreased as the accessibility to neighbourhood destinations increased (logit model). Effect sizes continued to decrease in model 3, indicating a potential mediating effect of the covariates. In contrast to results for model 2, the AIC values in model 3 were lowest for the NDAI based on method 2, not only at 800m but also at 1600m. However, the NDAI based on method 3 retained the lowest AIC value at 2400m indicating model superiority at this neighbourhood level. In addition, when comparing which NDAI method and spatial level is the best at predicting associations with walking to work, the NDAI based on method 3 at 2400m, has the lowest AIC value in comparison to all other models (AIC=7714.70) and is markedly lower than the next nearest AIC value (7835.47).

Table 36. Zero-inflated negative binomial model of associations between walking to work and the NDAIs, adjusted for proxies of age, ethnicity and sex, (model 2), and additionally adjusted for proxies of education, household income, access to a car and area deprivation (model 3).

Walking to work	Percent change[a] in walking to work (95% CI) (negative binomial model)		Odds ratio [b] for being a non-participant in walking to work (95% CI) (logit model)		
	Model 2 (adjusted for age, ethnicity and sex)				
	Percent change	**CI (95%)**	**OR**	**CI (95%)**	**AIC**
NDAI Method 2					
800m	**1.05**	**1.04-1.05**	**0.90**	**0.88-0.92**	8723.56
1600m	**1.05**	**1.05-1.06**	**0.92**	**0.90-0.93**	8534.83
2400m	**1.04**	**1.04-1.04**	**0.94**	**0.92-0.95**	8848.05
NDAI Method 3					
800m	**1.03**	**1.03-1.04**	**0.92**	**0.91-0.93**	8765.16
1600m	**1.05**	**1.05-1.06**	**0.88**	**0.86-0.90**	8517.83
2400m	**1.06**	**1.06-1.07**	**0.88**	**0.86-0.90**	8346.81
	Model 3 (additionally adjusted for education, household income, access to a car and area deprivation)				
NDAI Method 2					
800m	**1.03**	**1.02-1.03**	**0.93**	**0.91-0.95**	7968.20
1600m	**1.03**	**1.03-1.04**	**0.95**	**0.93-0.97**	7835.47
2400m	**1.02**	**1.02-1.03**	**0.96**	**0.95-0.98**	7963.07
NDAI Method 3					
800m	**1.02**	**1.01-1.02**	**0.95**	**0.93-0.96**	7979.29
1600m	**1.04**	**1.03-1.04**	**0.92**	**0.89-0.94**	7840.64
2400m	**1.05**	**1.04-1.05**	**0.92**	**0.90-0.95**	7714.70

Values highlighted in bold indicate statistically significant associations ($p<0.001$) and shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in walking to work per unit increase in neighbourhood destination accessibility. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in walking to work associated with a unit increase in neighbourhood destination accessibility.

6.4.4 Bikeability and cycling to work

Cycling as an active transport mode is quite different to walking, longer distances can be travelled and it requires a piece of human powered equipment, the bike, in order to get from one destination to another. Consequently, it is important to measure associations between cycling and specific features of the built environment which are theorised to encourage or hinder the behaviour, which can be different to features that influence walking. This section attempts to address the gap in existing research on the built environment which is primarily concerned with measuring walkability, with only a few studies objectively measuring bikeability (Winters et al., 2010; Winters et al., 2013). Associations between the objectively derived Bike Indices (methods 2 and 3) and cycling to work are investigated using the following research questions:

A) Does the frequency of cycling to work increase as the bikeability of the built environment increases?

B) Do the probabilities of being a non-participant in cycling to work decrease as the bikeability of the built environment increases? And how does this relationship vary depending on neighbourhood definition and scale after controlling for potential confounding covariates?

Results for Model 1

Descriptive statistics and the results for the unadjusted bivariate ZINB model are presented (Table 37). As expected, there are differences in the mean values and standard deviations for both methods across the three spatial scales. Even though the effect sizes were negligible, there was a significant positive association between the bikeability of the built environment and cycling to work at 1600m and 2400m for the BI based on method 2 (NB model). The BI based on method 3 was also significantly associated with cycling to work, but only at the 2400m neighbourhood scale (NB model). Unsurprisingly, there was no association between cycling and bikeability at the 800m level, possibly because it is too short a distance to capture cycling behaviour. In the logit model, a unit increase in the bikeability of the built environment was significantly associated with decreased odds of being a non-participant in cycling for both methods of BIs at each neighbourhood level. Effect sizes were marginal, but significant across all spatial levels.

Based on the AIC model fit scores, the BI based on method 2 at 1600m and 2400m and the BI based on method 3 at 800m were the best models for predicting bivariate associations. However, the percent change is equal to 1 for the BI based on method 3 at 800m, indicating no relationship. Comparing AIC values between both methods and at all scales, the BI based on method 2 at 2400m has the lowest AIC value in comparison to all other models, indicating that it is the best fit to predict the relationship between cycling to work and the bikeability of the built environment.

Table 37. Unadjusted bivariate, zero-inflated negative binomial model of associations between cycling to work and indices of Bikeability.

Cycling to work			Percent change[a] in walking to work (95% CI) (negative binomial model)			Odds ratio [b] for being a non-participant in cycling to work (95% CI) (logit model)		
					Model 1			
	Mean	(Std)	Percent change	CI (95%)		OR	CI (95%)	AIC
BI Method 2								
800m	29.76	5.91	1.00	0.99-1.01		0.98*	0.96-0.99	5549.04
1600m	27.97	5.26	**1.01**	**1.01-1.02**		0.95***	0.93-0.97	5511.93
2400m	26.50	5.48	**1.02**	**1.01-1.02**		0.93***	0.91-0.95	5475.90
BI Method 3								
800m	31.30	6.86	1.00	0.99-1.01		0.98*	0.97-0.99	5547.68
1600m	31.19	5.64	1.01	1.00-1.01		0.98**	0.96-0.99	5542.52
2400m	30.82	4.63	**1.01**	**1.00-1.02**		0.96***	0.94-0.98	5532.64

Values in highlighted bold indicate statistically significant associations at p<0.001; *=significance associations at p<0.05 and **= significance at p<0.01. Shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in cycling to work per unit increase in neighbourhood bikeability. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in cycling to work associated with a unit increase in neighbourhood bikeability.

Results for Models 2 and 3

The results of model 2, (adjusted for proxies of age, ethnicity and sex) and model 3, (additionally adjusted for proxies of education, household income, access to a car and area deprivation) are presented (Table 38). There was a statistically significant positive association between cycling to work and the bikeability of the built environment in model 2 for all spatial levels. However, with the model 3, the BIs based on methods 2 and 3 at 800m had no association, while the both methods at 1600m and 2400m were associated with cycling to work. The results for both models were remarkably similar, with effect sizes remaining small, ranging from 1%-2% (NB model). For the logit model, both model 2 and 3 had very similar results, with statistically significant negative associations with the bikeability of the built environment. Furthermore, while the results for the NB model in model 1 remained much the same; the results for the logit model had lower ORs and AIC values across both methods and spatial levels in models 2 and 3. This indicates that the models improve after controlling for the covariates.

Finally, when comparing each method the results are similar to model 1, in which the BI based on method 2 had the lowest AIC values with models 2 and 3 at 1600m and 2400m, indicating that this method was the best fit for the data. Also, the BI based on method 3 had the lowest AIC value at the 800m spatial level. When comparing all AIC values, the BI based on method 3 had the lowest AIC values at 2400m neighbourhood level, indicating it was the best fit model to predict associations with the outcome cycling to work.

Table 38. Zero-inflated negative binomial model of associations between cycling to work and the Bike Indices, adjusted for proxies of age, ethnicity and sex, (model 2), and additionally adjusted for proxies of education, household income, access to a car and area deprivation (model 3).

Cycling to work	**Percent change[a] in cycling to work (95% CI) (negative binomial model)**		**Odds ratio [b] for being a non-participant in cycling to work (95% CI) (logit model)**		
	Model 2 (adjusted for age, ethnicity and sex)				
	Percent change	**CI (95%)**	**OR**	**CI (95%)**	**AIC**
BI Method 2					
800m	1.01*	1.00-1.02	**0.95**	**0.92-0.97**	5237.80
1600m	**1.02**	1.01-1.03	**0.92**	**0.90-0.94**	5195.92
2400m	**1.02**	1.01-1.03	**0.91**	**0.89-0.94**	5174.76
BI Method 3					
800m	1.01*	1.00-1.01	**0.95**	**0.93-0.97**	5231.57
1600m	1.01**	1.01-1.02	**0.95**	**0.92-0.97**	5230.87
2400m	**1.02**	1.01-1.03	**0.93**	**0.90-0.96**	5221.90
	Model 3 (additionally adjusted for education, household income, access to a car and area deprivation)				
BI Method 2					
800m	1.01	0.99-1.02	**0.95**	**0.92-0.98**	5187.00
1600m	**1.02**	1.01-1.03	**0.92**	**0.89-0.95**	5154.47
2400m	**1.02**	1.01-1.03	**0.92**	**0.89-0.94**	5139.38
BI Method 3					
800m	1.01	0.99-1.01	**0.95**	**0.93-0.98**	5183.01
1600m	1.01**	1.00-1.02	**0.95**	**0.92-0.98**	5184.03
2400m	**1.02**	1.01-1.03	**0.93**	**0.90-0.97**	5176.90

Values highlighted in bold indicate statistically significant associations at $p<0.001$; *=significance associations at $p<0.05$ and **= significance at $p<0.01$. Shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in cycling to work per unit increase in neighbourhood bikeability. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in cycling to work associated with a unit increase in neighbourhood bikeability.

6.4.5 Neighbourhood destination accessibility and cycling to work

Identifying the components of the built environment that could promote or hinder all types of cycling, such as leisure, utilitarian and transport are necessary to improve health outcomes. Having attractive destinations to cycle to such as cafés and shops or pass through such as the park, while on the way to work, could potentially encourage this type of cycling behaviour. The next section investigates if there is a relationship between cycling to work and neighbourhood destination accessibility by applying the following research questions:

A) Does the frequency of cycling to work increase as the accessibility of neighbourhood destinations increases?

B) Are the odds of being a non-participant in cycling to work inversely proportional to the accessibility of neighbourhood destinations? And how does this vary depending on neighbourhood definition and scale after controlling for potential confounding covariates?

The results for models 1, 2 and 3 are presented in Table 39 and show that the associations between neighbourhood destination accessibility and cycling to work range from no association (1.00) to a marginal association (1.01), and even a negative association (0.99) in the NB models. In the logit models, however, associations across all three models were consistently, statistically significant in the expected direction (less than 1), and generally had improved ORs as each subsequent model was additionally controlled for. This suggests that as neighbourhood destination accessibility increases, (for both NDAI methods 2 and 3), the odds of being a non-participant in cycling to work decrease for models 1, 2 and 3.

Focusing on the fully adjusted model, (model 3), the NDAI based on method 2 at 1600m neighbourhood level, while marginal, was the only method significantly positively associated with cycling to work, all other spatial levels had either no association or a negative association with the NDAI based on method 3. In other words, for every unit increase in neighbourhood destination accessibility (as defined by the NDAI based on method 2 at 1600m) cycling frequency increased by 1%. In contrast, both methods at all spatial levels were significantly associated with the odds of being a non-participant in cycling to work. Taking the example of NDAI based on method 3, a unit increase in the neighbourhood destination accessibility was associated with an estimated 3% decrease in the odds of being a non-participant in cycling to work. Finally, the AIC values continued to decrease as each model was adjusted for potential confounders. In model 3, when comparing between methods 2 and 3, the NDAI based on method 2 had the lowest AIC values at 800m and 1600m neighbourhood levels, and the NDAI based on method 3 had the lowest AIC values at the 2400m scale, indicating best model fit for the data. If all AIC values are compared across methods and scales, the NDAI based on method 2 (Euclidean buffer) at 1600m has the lowest overall AIC value (5185.26), suggesting it is the best fit model when measuring associations between neighbourhood destination accessibility and cycling to work.

Table 39. Model 1 results of unadjusted bivariate, zero-inflated negative binomial model of associations between cycling to work and indices of Neighbourhood Destination Accessibility; model 2 is additionally adjusted for proxies of age, ethnicity and sex; and model 3, is additionally adjusted for proxies of education, household income, access to a car and area deprivation.

Cycling to work	Percent change[a] in cycling to work (95% CI) (negative binomial model)			Odds ratio [b] for being a non-participant in cycling to work (95% CI) (logit model)		
Model 1						
	Percent change	**CI (95%)**		**OR**	**CI (95%)**	**AIC**
NDAI Method 2						
800m	1.00	0.99-1.00		**0.99**	0.98-0.99	5544.39
1600m	1.00*	1.00-1.01		**0.98**	0.97-0.99	5524.54
2400m	1.00*	1.00-1.01		**0.97**	0.96-0.98	5511.70
NDAI Method 3						
800m	0.99	0.99-1.00		0.99**	0.98-0.99	5545.27
1600m	1.00	0.99-1.00		**0.98**	0.97-0.99	5537.74
2400m	1.00	0.99-1.01		**0.97**	0.96-0.98	5523.92
Model 2 (adjusted for age, ethnicity and sex)						
NDAI Method 2						
800m	1.00	0.99-1.01		**0.97**	0.96-0.98	5239.78
1600m	1.01**	1.00-1.01		**0.97**	0.960.98	5225.39
2400m	1.00*	1.00-1.01		**0.97**	0.96-0.98	5237.80
NDAI Method 3						
800m	1.00	0.99-1.00		**0.98**	0.97-0.99	5242.26
1600m	1.00	0.99-1.01		**0.97**	0.96-0.98	5238.16
2400m	1.00	0.99-1.01		0.98**	0.97-0.99	5192.29
Model 3 (additionally adjusted for education, household income, access to a car and area deprivation)						
NDAI Method 2						
800m	1.00	0.99-1.01		0.97**	0.96-0.99	5193.05
1600m	1.01*	1.00-1.01		**0.97**	0.96-0.99	5185.26
2400m	1.00	0.99-1.01		0.98**	0.97-0.99	5192.29
NDAI Method 3						
800m	0.99	0.99-1.01		0.98**	0.97-0.99	5195.14
1600m	1.00	0.99-1.01		0.98*	0.96-0.99	5195.25
2400m	1.00	0.99-1.01		**0.97**	0.95-0.99	5189.01

Values highlighted in bold indicate statistically significant associations at p<0.001; *=significance associations at p<0.05 and **= significance at p<0.01. Shaded cells indicate the best fitting model based on the AIC values. [a] Negative binomial model represents the percent change in cycling to work per unit increase in neighbourhood destination accessibility. [b] Logit model represents the proportional increase or decrease in the odds of being a non-participant in cycling to work associated with a unit increase in neighbourhood destination accessibility.

6.5 Summary of findings

6.5.1 Built environment influences on walking to work

Walkability and walking to work

The results of the bivariate analysis indicated strong, statistically significant positive associations between walkability, as defined by both the BWIs and the EWIs, and walking to work for all three neighbourhood levels (800m, 1600m and 2400m). In addition, the odds of being a non-participant in walking to work are significantly negatively associated with a unit increase in all walk indices (BWIs and EWIs), for all spatial levels.

Comparing between the standard BWI (method 1), and the novel BWIs (method 2 and 3), the BWI based on method 3, (network buffers) had the strongest associations, for predicting both walking to work, and significant decreased odds of being a non-participant in walking to work as the walkability of the built environment increased. The 800m and 1600m neighbourhood areas based on network buffers had the strongest associations and the lowest AIC values in comparison to all other models, indicating model superiority. In contrast, the BWI based on the standard method (network buffer) had the lowest AIC value, in comparison to all other BWI methods at the 2400m neighbourhood level. Both methods 1 and 3, while created using simple intensity and kernel density methods, are comparable as they both used network buffers.

Comparing the EWI methods 2 and 3, the novel method based on network buffers (method 3), had the strongest positive associations with walking to work at all three spatial levels. When comparing between the BWIs and the EWIs, both EWIs were better models at predicting associations (based on the AIC values), and the EWI based on method 3 had the lowest AIC values across all three spatial levels. Within the EWI based on method 3, the 800m neighbourhood level had the strongest positive associations with walking to work, and decreased odds in being a non-participant in walking to work for a one unit increase in the walk index, indicating that the novel EWI, network buffer at 800m, is the best model at predicting associations with walking.

After adjusting for proxies of demographic covariates, age, sex, and ethnicity, significant positive associations between the walkability of the built environment based on all indices methods, and frequency of walking to work remained. However in comparison to the unadjusted model 1, within the BWIs, the BWI based on method 3 was a better model fit for all three neighbourhood levels (800m, 1600m and 2400m), rather than BWI based on the standard method. The EWIs were, again, the strongest indices in predicating associations with walking to work. In particular the EWI based on the novel method 3, network buffer, had significant positive associations at all three spatial levels, with the 800m level being the best predictor.

Finally, in the fully adjusted model, (model 3), significant positive associations remained between all the walkability indices and walking to work. While the effect sizes decreased in comparison to the bivariate and demographically adjusted models, the BWI based on method 3, remained the best predicted model in comparison to all the BWIs. For example, the BWI based on method 3 at 800m, predicted an estimated 34% increase in walking frequency to work for every unit increase in the walk index, in comparison to 11% and 16% for BWI methods 1 and 3. In addition, for this specific index (BWI method 3), a unit increase in walkability was associated with a 30% decreased odds of being a non-participant in walking to work, in comparison to 14% decreased odds for both BWI, method 1 and 2. Based on the AIC values of the BWIs based on method 3, the 800m network buffer, followed by the 2400m network buffer and lastly the 1600m network buffer were the best fit models.

Comparing between the EWIs in the fully adjusted model, again, the EWI based on method 3, at all three neighbourhood levels was the superior method at predicting positive associations between walking to work and the walk index. In addition, EWI, based on method 3, in comparison with the BWIs was, overall, the best index and method in predicting associations. Effect sizes were larger than the other BWIs and the AIC values were lowest for this index and method. For example, the EWI based on method 3 was associated with an estimated 40% increase in walking frequency for both the 800m and 1600m neighbourhood areas, and a 36% increase in walking frequency for the 2400m for every unit increase in the walk index. In addition, every unit increase in the walk index was associated with a 39% decreased odds at 800m, a 34% at 1600m and a 25% at 2400m of being a non-participant in walking to work.

These results reveal a number of important findings. Firstly, that the BWI based on method 1, (standard approach, network buffer), is associated with walking to work and predicting decreased odds of non-participants walking to work for a unit increase in the walk index. This finding lends further validity to previous research which has found associations between this type of walk index and walking for transport (Mayne et al., 2013). Secondly, the newly created methods in this thesis, the kernel density based methods with Euclidean and network buffers, (methods 2 and 3 respectively), are also significantly positively associated with walking to work, and predicting the odds of being a non-participant in walking to work for both the BWIs and the EWIs. These results indicate that the novel methods are also valid and are more strongly, in terms of effect sizes, associated with the predicting walking for transport. These results could signify previous research has underestimated or downplayed the significant impact the built environment can have on encouraging walking to work. The more nuanced novel indices present stronger evidence linking the built environment and walking which can be used to inform and strengthen arguments for policies and planning decisions to encourage walkability. Thirdly, when comparing between the BWIs and the EWIs, method to method, overall the EWIs, which are composed of measures of land use mix, street connectivity, dwelling density, footpaths and tracks, street lights and slope, performed better, lending credibility that these indices capture or explain more of the contextual built environment than the BWIs which only contain three components, measures of land use mix, street connectivity and dwelling density. Fourthly, comparing between the type of buffer used, while both buffers were consistently significantly positively associated with walking to work, the network buffer, (method 3) had the largest effect sizes and the lowest AIC values, in comparison to the Euclidean buffer (method 2). Finally, these results in the fully adjusted model, suggest that the 800m network based buffer created using the kernel density method (method 3), is the best predictor of walking to work, followed by the 2400m and then the 1600m based on AIC values. This finding suggests that living in a walkable area within a 10 minute walk (800m) could potentially encourage active transport behaviours such as walking to work.

Neighbourhood destination accessibility and walking to work

In the unadjusted models, both NDAI methods were significant and positively associated with walking to work across all neighbourhood levels, although effect sizes were small, ranging from 6-8% (the NB models). In the logit models, both NDAIs were significant ($p<0.001$) and negatively associated with decreased odds of being a non-participant in walking to work, with effect sizes small, ranging from OR 0.89, to OR 0.93. Comparing between both methods, the AIC values were lowest at the 800m scale for the novel method 2 (Euclidean buffer), while the AIC values were lowest at the 1600m and 2400m scales for the KDE network buffers (method 3). The NDAI based on method 3 at 2400m neighbourhood level had, overall, a markedly lower AIC value (9197.82) in comparison to all other models, indicating model superiority.

For both the NB model and the logit model, the NDAIs based on method 2 and 3, results remained largely the same after adjusting for proxies of age, sex, and ethnicity. Effect sizes reduced further, indicating potential confounding. In addition, the AIC values, which penalises model complexity (Beaujean and Morgan, 2016), continued to decrease after adding covariates. Comparing between the methods, again, the NDAI based on method 2, at 800m had the lowest values and the NDAI based on method 3 had the lowest AIC values at 1600m and 2400m neighbourhood levels. Comparing both methods and all spatial levels, the 2400m neighbourhood level based on method 3 performed the best, based on the AIC values.

Finally, in the fully adjusted model, the results were very similar to models 1 and 2, although the inclusion of potential confounders continued to decrease the effect sizes, which ranged from 2%-5% in the NB model and the ORs ranged from 0.92-0.96 in the logit models. Importantly, the associations between walking to work and neighbourhood destination accessibility remained statistically significant ($p<0.001$), even after additionally adjusting for proxies of education, household income, access to a car and area deprivation. Comparing AIC values between the methods, to determine which method performed the best, the NDAI based on the Euclidean buffers (method 2) had the lowest AIC values at both 800m and 1600m, whereas the NDAI based on the network buffer (method 3) was only significant at the 2400m neighbourhood level. However, comparing all models and neighbourhood levels, the NDAI based on method 3 at 2400m, similar to the unadjusted and demographically adjusted models, remained the best fit model for the data with a markedly lower AIC value (7714.70) in comparison to all other models (7968.20; 7835.47; 7963.07; 7979.29 and 7840.64).

The results of this analyses indicate there are significant associations between the NDAIs and walking to work, however, the effect sizes are small and should therefore be interpreted with caution. This finding is unsurprising as the outcome variable, walking to work, is a specific physical activity with a direct purpose i.e. to get to work, whereas neighbourhood destination accessibility is potentially less relevant to walkers for transport. In addition, due to the limitation of the outcome data available, it was not possible to test the relationship between the NDAIs and all types of walking both separately and together, such as walking for leisure and walking for transport. However, it was still important to test the hypothesis that neighbourhood destination accessibility could influence walking to work. Creating attractive built environments to walk through by having destinations such as shops, restaurants and cafés could encourage walking to and from work.

6.5.2 Built environment influences on cycling to work

Bikeability and cycling to work

Similar results were reported in all three models. Measures of bikeability were associated with cycling to work, however effect sizes were small, where both methods in the NB model predicted only 1%-2% of the variance. In the unadjusted bivariate model, there was no association between cycling to work and bikeability for either method at 800m. However, in the logit model, the odds of being a non-participant in cycling decreased as the bikeability of the built environment increased and this was significant across all neighbourhood scales, ORs ranging from 0.93-0.98.

After adjusting for proxies of age, sex, and ethnicity, the BIs based on methods 2 and 3 at 800m became statistically significant predicting a 1% change. However, such small effect sizes need to be interpreted with caution. There was a marginal increase of 1% between model 1 and model 2 for both methods at 1600m and 2400m, such a negligible increase indicates that demographic factors have a minimal to zero effect on whether people cycle to work. Similarly, in the logit model, the ORs decrease further and range between 0.91 and 0.95 across all neighbourhood levels. When comparing AIC values between methods, the BI based on method 2 (Euclidean buffer) at 1600m and 2400m, and the BI based on method 3 (network buffer) at 800m had the lowest values.

In the fully adjusted model, the results were almost identical to model 2, with a couple of exceptions, the BI methods 2 and 3 at 800m were not associated with cycling to work. However, both methods at all neighbourhood levels were significantly negatively associated with being a non-participant in cycling to work for a unit increase in either bikeability index. Again, the results of models 2 and 3 are similar, indicating there is little to no confounding influence of the additional covariates, proxies of education, household income, vehicle ownership, and area deprivation. However, the AIC values continued to decrease, and as mentioned previously, AICs penalise model complexity. Comparing between both models, the BI based on method 2 at 1600m and 2400m had again the lowest AIC values, whereas the BI based on method 3 at 800m had the lowest value. Finally, if all AIC values are to be compared in order to determine the best fit model, the BI based on the Euclidean buffer at 2400m had the lowest value.

These results are somewhat interesting for a number of reasons. Firstly, there were limitations to the bike index, both the components included and those unable to include. The measures included, such as, the density of cycle tracks in Wellington, was very limited in its coverage of the city. Other bicycle infrastructure such as separated bike paths and bike storage were not included due to the data being publicly unavailable. Secondly, the bike index contains components of the walk index which are potentially not relevant for cycling such as dwelling density. Thirdly, while there still was an association found between the bike indices and bikeability, contrary to expected results, the Euclidean based bike index performed the best for both the 1600m and 2400m neighbourhood level. This is unexpected as cycling is presumed to follow the street network. Finally, no association was found at 800m between cycling to work and the bikeability of the built environment. This is unsurprising as it could be argued that in order to cycle to work the distance has to be greater than a 10 minute walk. Distances greater than 2400m should be examined in future research, as cycling often takes place over longer distances than walking (Winters et al., 2010).

NDAI and cycling to work

Overall, in each of the models, even after adjusting for potential confounders, there was little to no association between the NDAIs, both methods, and estimating cycling to work. However, in the logit models, there was a consistent pattern of significant associations across all three models. The ORs were small and ranged from 0.97-0.99. Because the models changed only slightly, even after adjusting for demographic, socio-economic and deprivation covariates, indicates these have no confounding relationship with cycling to work and the neighbourhood destination accessibility indices. Due to the overall small effect sizes across all models, the analyses reveal that neighbourhood destination accessibility does not influence cycling to work.

6.6 Conclusion

This chapter investigated associations between indices of the built environment, for walkability, bikeability and neighbourhood destination accessibility and active modes of transport. Findings related to the BWI based on the standard method, (network buffer), were consistent with previous research. New findings, in relation to the more nuanced methods of using kernel density to measure the built environment, also found significant associations with walking and cycling to work. Results for walking to work had the strongest associations with the novel method based on the network buffer (method 3), with AIC values indicating best fit model.

Results for the NDAI methods and walking and cycling to work were, in general, significantly associated, although with small effect sizes. In the case of walking, including other types of walking such as walking for leisure in the analysis could potentially yield stronger associations. The results of the bikeability indices and cycling to work, while associated in the expected direction, the effect sizes were also small and need to be interpreted with caution.

While the newly created novel indices (BIs and NDAIs) presented in this thesis did not predict cycling to work as strongly as expected, the novel indices of walkability predicted moderate to strong associations with walking to work. In addition, the neighbourhood destination accessibility indices too, predicted associations with walking to work, despite having small effect sizes. Importantly, the methods used to create the indices and in particular the novel method 3, (network buffer), present an opportunity for more nuanced approach to measuring the built environment for active transport. The results presented in this chapter support further application and replication of this new approach, potentially lending validity to these findings.

The following chapter, Chapter 7, describes and analyses the associations between these indices of the built environment, physical activity and overweight/obesity, utilising data from the New Zealand Health Survey.

Chapter 7. Measuring Associations between Indices of the Built Environment, Physical Activity and Health Outcomes

7.1 Introduction

Physical activity is important for protecting against heart disease, stroke, type 2 diabetes, certain types of cancers and also counteracting diseases such as obesity (Ministry of Health, 2015a). Over the last two decades, the built environment has been increasingly investigated for influencing physical activity behaviours and related health outcomes such as overweight and obesity. Identifying characteristics of the neighbourhood built environment that deter or encourage physical activity, and how these may be associated with overweight and obesity, is a necessary step in order to make improvements to existing built environments, and review current urban planning policy.

This chapter addresses the tenth objective, which is to investigate the associations of indices of the built environment (described in Chapters 3 and 4), physical activity and health-related outcomes using data from the New Zealand Health Survey (NZHS). A description of the study data, independent variables and covariates used in the analyses follows (section 7.2), then a description of the statistical analyses procedure is presented (section 7.3). The results of associations between the Basic Walk Indices (BWIs), Enhanced Walk Indices (EWIs), Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs) and physical activity and overweight/obesity are presented with relevant research questions at the beginning of each results section to guide the analysis (section 7.4). The chapter concludes with a summary of the main findings arising from the analyses (section 7.5).

7.2 Methods

Study data

The NZHS was used to validate and test associations between the built environment, physical activity and overweight/obesity. The survey is a nationally representative sample of New Zealand residents and has a multi-stage, stratified, probability-proportional-to-size sampling design (Ministry of Health, 2015c). Households are systematically selected within meshblocks, using a skip algorithm (Ministry of Health, 2015c). The interviewer-administered survey collects information on health status, long-term health conditions, health behaviours and risk factors, (e.g. physical activity, tobacco use and alcohol consumption), nutrition, mental health, oral health, health service utilisation, patient experience and socio-demographic data (Ministry of Health, 2015d). Objective measurements of participants' height, weight and waist are taken at the end of the interview using a professional laser meter, electronic weighing scales and an anthropometric measuring tape (Ministry of Health, 2015c). The sample is collated at the meshblock area unit, and areas with ethnic minority groups are over-sampled to provide sufficient sample sizes for analyses (Ministry of Health, 2015c). Initially, the survey was completed every 6 years; however, it has been completed yearly since 2011/12 up to year 2014/15. As an example of the general sample size of the survey conducted each year, the 2014/15 survey collected information from 4,754 children (aged 0-14) and 13,497 adults (aged over 15 years) (Ministry of Health, 2015a). Sample sizes for Wellington City were relatively small, n=460 in the 2011/12 survey, n=479 in 2012/13, n=650 in 2013/14, and n=508 in the 2014/15 survey. In order to increase the statistical power for analyses, data from each year between 2011 to 2015 was combined to create a total sample size of 2,097 individuals.

7.2.1 Individual level health outcome data

Two health outcomes from the NZHS were used to validate and investigate associations with indices of the built environment for walking, cycling and neighbourhood destination accessibility.

Physical activity

Survey participants were asked about their physical activity behaviours in the preceding seven days. The Ministry of Health defined physical activity as adults aged 15 or older doing at least 30 minutes of brisk walking[2] or moderate-intensity physical activity (or equivalent vigorous activity), lasting at least 10 minutes at a time, on five days of the previous week (Ministry of Health, 2015e). Examples of moderate-intensity physical activity include heavy housework, (cleaning windows) or gardening (manual lawn-mowing), cycling at a regular pace; vigorous activity examples include heavy lifting, running, fast cycling, touch rugby or chopping wood (Ministry of Health 2015e). Based on a range of answers regarding time spent on physical activity, the Ministry of Health (2015e), created a combined measure of physical activity.

[2]Brisk walking is defined as a walking pace at which you are breathing harder than normal (Ministry of Health, 2015d).

The formula used to calculate the combined measure is:

Time spent doing brisk walking in the past 7 days + time spent doing moderate exercise in the past 7 days + 2 x (time spent doing vigorous activity in the past 7 days) (Ministry of Health, 2015e).

This measure was used to create a binary variable, where (1) represented individuals that met the physical activity guidelines and (0) represented individuals who did not. This measure was one of the dependent variables used to test associations with indices of the built environment developed in this research.

Body Mass Index (BMI)

Each respondents BMI was calculated by obtaining objective measurements of their height, weight and waist diameter. According to the World Health Organisation, (WHO, 2016), individuals with a BMI of greater than or equal to 25 are considered overweight and individuals with a BMI greater than 30 are considered obese. Due to the small number of obese individuals in the sample, a binary measure of (1) representing overweight/obese individuals (BMI ≥ 25) and (0) representing 'healthy' weight individuals was created (BMI < 25). The BMI measure was included as the second dependent variable to test associations with indices of the built environment.

7.2.2 Individual level covariates

Age

Age data was provided in a number of age groups ranging from 15-75+ years old. To simplify the interpretation of results and ensure consistency with related research (Witten et al., 2012), five age groups were created to represent more broadly individuals at different stages in their lives. These groups were 15-29 years, 30-44 years, 45-54 years, 55-64 years and 65 years and over. Witten et al., (2012) did not include the final age group of 65 and over; however, this research is interested in the influence of walkability and bikeability across all age groups. Furthermore, previous research into the built environment and walkability for older adults is an emerging field and associations vary by age groups (Grant et al., 2010; Procter-Gray et al., 2015; Van Cauwenberg et al., 2016; Van Holle et al., 2014).

Sex

The proportion of males to females was included as a covariate and potential confounder. Research focusing on links between the built environment, physical activity and overweight/obesity, regularly control for the potential influence of sex (Frank et al., 2007; Witten et al., 2012; Pearson et al., 2014; Oliver et al., 2015).

Ethnicity

The sample for Wellington City included four ethnic groups, Māori, Pacific, Asian and European/Other. In New Zealand, ethnic minorities, especially Māori and Pacific Islanders have higher rates of health risks such as being physically inactive, smoking, obesity, hazardous drinking and psychological distress than non-Māori and non-Pacific adults (Ministry of Health, 2015a). Research measuring associations between the built environment, physical activity and overweight/obesity regularly includes ethnicity as a potential confounder (Witten et al., 2012; Pearson et al., 2014). Ethnicity was included as a categorical variable in the analysis.

Socio-economic covariates

Information regarding individuals' education, employment status, and household income, were obtained from the self-reported NZHS. Each of these was included as covariates as used in previous research (Witten et al., 2012) in order to control for potential confounders. Similar to Witten et al., (2012), education was grouped into five categories, 1= no qualifications, 2= high school qualifications, 3= post-school qualifications, 4= undergraduate university degree, and 5= postgraduate university degree; employment was reduced to three categories, 1= employed, 2= unemployed, and 3= unemployed and not looking for work (for example, caregiver/student); household income was grouped into five categories, 1= less than NZ$40,000, 2= NZ$40,001-60,000, 3=NZ$60,001-70,000, 4= NZ$70,001-100,000 and 5= greater than NZ$100,000.

7.2.3 Area level covariate

Deprivation

Measures of deprivation are regularly included in health research to account for confounding (Van Lenthe and Mackenbach, 2002; Witten et al, 2012; Pearson et al., 2014). The New Zealand Index of Deprivation (NZDep13; Atkinson et al., 2014) is an area level measure of deprivation. It is made up of nine variables from 2013 New Zealand Census and includes: access to the internet, equivalised household income, means tested benefits, employment, single parent families, qualifications, home ownership, access to a car and household overcrowding (Atkinson et al., 2014), previously described in Chapter 5, section 5.2.3). Similar to previous research in New Zealand, (Witten et al., 2012; Pearson et al., 2014) the NZDep13 was classified into quintiles and included as a potential confounding measure of area level deprivation.

7.2.4 Built environment exposure measures

The Basic Walk Indices (BWIs), Enhanced Walk Indices (EWIs), Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs) based on methods 1, 2 and 3 (described in Chapter 3, sections 3.7.1 and 3.7.2) will be analysed in this chapter to test for associations with physical activity behaviours and overweight or obesity health outcomes. The composite indices of the built environment created as part of this research, were sent to the Ministry of Health in order to be linked with individual level health data. The meshblock identifier was removed after joining the datasets to maintain confidentiality of the individuals' health data. This is required in health-related research, in order to meet ethical standards.

7.3 Statistical analyses

Descriptive statistics were calculated for each of the health outcomes of interest and each of the built environment indices. The minimum, maximum, mean, median and standard deviations were then compared. The strength of associations between the indices of the built environment and health-related variables were examined using logistic regressions. Logistic regression models are commonly used when the outcome variable is dichotomous and the exposure variables are continuous or categorical data (Gattrell, 2002). Negative binomial logistic models using the generalised linear model (glm) function in *R* (R Development Core Team, 2014), with the response variable generated from the binomial exponential family of distribution, (UCLA, 2016), was used to estimate associations. Due to the restriction of using unidentifiable individual data from the NZHS, it was not possible to complete multilevel analyses of participants nested within neighbourhoods.

A number of bivariate and multivariate negative binomial regression models were used to determine associations between the BWIs, EWIs, BIs and NDAIs, physical activity and overweight/obesity. For each index at each spatial level, (800m, 1600m and 2400m), four models were completed. Table 40 presents an overview of the models applied and the potential confounder variables additionally included in models 2, 3 and 4.

Table 40. Example table of multiple models applied to test for associations between outcome and exposure variables using binomial logistic regression models.

	Model 1 [a]: Unadjusted bivariate models	**Model 2 [b]: Adjusted for demographics**	**Model 3 [b]: Adjusted for socio-economic**	**Model 4 [b]: Adjusted for area deprivation**
Outcome variables [a]	**Exposure variables**	**Exposure variables**	**Exposure variables**	**Exposure variables**
Physical activity	- BWIs (methods 1, 2 & 3) - EWIs - BIs - NDAIs (methods 2 & 3)	BWIs (methods 1, 2 & 3) - EWIs - BIs - NDAIs (methods 2 & 3)	BWIs (methods 1, 2 & 3) - EWIs - BIs - NDAIs (methods 2 & 3)	BWIs (methods 1, 2 & 3) - EWIs - BIs - NDAIs (methods 2 & 3)
		Age: - 15-29 - 55-64 - 30-44 - ≥65 - 45-54	**Age:** - 15-29 - 55-64 - 30-44 - ≥65 - 45-54	**Age:** - 15-29 - 55-64 - 30-44 - ≥65 - 45-54
		Ethnicity: - Māori - Pacific - Asian - European/Other	**Ethnicity:** - Māori - Pacific - Asian - European/Other	**Ethnicity:** - Māori - Pacific - Asian - European/Other
		Sex: - Female - Male	**Sex:** - Female - Male	**Sex:** - Female - Male
			Education: - No qualifications - High-school qualifications - Post-school diploma/certificate - Undergraduate degree - Postgraduate degree	**Education:** - No qualifications - High-school qualifications - Post-school diploma/certificate - Undergraduate degree - Postgraduate degree
			Employment: - Employed - Unemployed - Unemployed, not looking for work	**Employment:** - Employed - Unemployed - Unemployed, not looking for work
			Household income: - ≤NZ$40,000 - NZ$40-60K - NZ$60-70K - NZ$70-100K - > NZ$100K	**Household income:** - ≤NZ$40,000 - NZ$40-60K - NZ$60-70K - NZ$70-100K - > NZ$100K
				NZ Deprivation: -Quintile 1 -Quintile 2 -Quintile 3 -Quintile 4 -Quintile 5

[a] The second outcome variable, overweight/obesity was also tested for associations with the Basic Walk Indices (BWIs), Enhanced Walk Indices (EWIs), Bike Indices (BIs) and Neighbourhood Destination Accessibility Indices (NDAIs) based on methods 2 and 3 at 800m, 1600m and 2400m spatial scales.
[b] Overweight/obesity was additionally controlled for potential confounders in models 2, 3 and 4.

As recommended by leading researchers in the field of environmental determinants (Leal & Chaix, 2011), a directed acyclic graph was used (Figure 60) to illustrate the hypothetical relationships and potential individual and neighbourhood confounders. Figure 60 is an example of the fully adjusted model for walkability and physical activity. The same model was repeated for the EWI, BI and NDAI built environment measures and models with the same confounders were used for overweight/obesity.

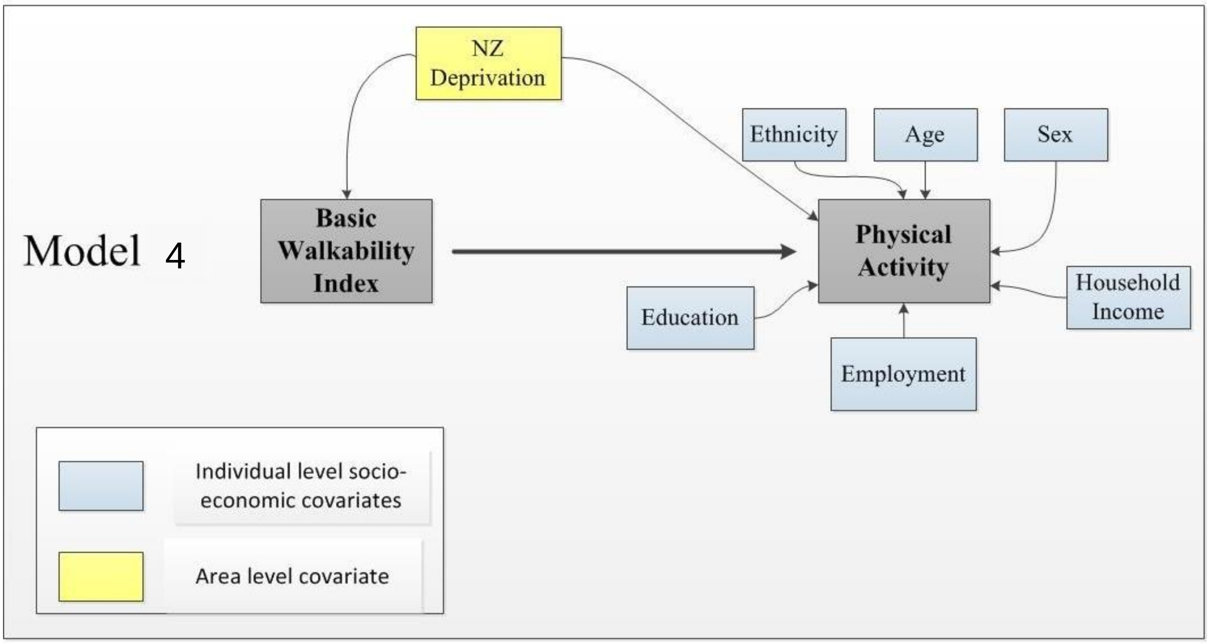


Figure 60. An example of a directed acyclic graph for a fully adjusted model (4), showing the theoretical relationships between exposure, outcome and potential confounder variables.

The results of logistic regression models are regularly interpreted by exponentiating the regression coefficients, placing the coefficients in an odds ratio (OR) scale. ORs with 95% confidence intervals (CIs) and bolded values in the tables indicate a statistically significant relationship based on p-values. In the physical activity regression models, values greater than one indicate a greater likelihood of meeting physical activity guidelines of 30 minutes on 5 or more days in a week. For example, an OR of 1.12 can be interpreted as: a unit increase in the walk (bike or neighbourhood destination) index is associated with an estimated 12% increase in the odds of meeting physical activity guidelines. In the overweight/obesity regression models, the hypothesised and expected relationships are: values less than one indicate decreased likelihood of being overweight or obese. For example, an OR of 0.75 can be understood as: a unit increase in the walk (bike or neighbourhood destination) index is associated with an estimated 25% decrease in the odds of being overweight/obese. Finally, all analyses were completed in *R* (R Development Core Team, 2014), a free software environment for statistical computing and graphics.

7.4 Results

7.4.1 Descriptive characteristics

The socio-demographic characteristics of the Wellington sample from the NZHS are presented (Table 41). The sample was composed of 57.1% females and 42.9% males. The highest ethnic group was European/Other, 71.5% followed by Asian (14%), Māori (10.5%) and Pacific (4%). The sample had a mix of qualifications, with the highest percentage (25.3%) obtaining an undergraduate university qualification. The lowest percentage age group was between the ages of 55 and 64, (12.5%), with the highest percentage age group between the ages 30 and 44, (31.9%). The highest percentage personal income was less than or equal to NZ$40,000 (32.9%), similar to the 2013 median personal income for Wellington city aged 15 or older, NZ$37,900 (Statistics New Zealand, 2015c). 66.8% of the sample were employed, while only 4.5% were unemployed and looking for work. The percentage of people living in the least deprived areas was much higher than the percentage of people living in the most deprived areas in this sample (28.5% vs. 7.2%).

Table 41. Socio-demographic characteristics of NZHS sample participants in Wellington City, including NZ deprivation index 2013 categories.

Variable	n (%)
Total n= 2097	
Age (years)	
15-29	471(22.5)
30-44	669(31.9)
45-54	384(18.3)
55-64	262(12.5)
>65	311(14.8)
Ethnicity	
Māori	220(10.5)
Pacific	83(4.0)
Asian	294(14.0)
European/Other	1500(71.5)
Sex	
Female	1198(57.1)
Male	899(42.9)
Qualification	
No high school qualification	495(23.7)
High school qualification	208(9.9)
Post-high school diploma or trade certificate	396(18.9)
University degree (Undergraduate)	531(25.3)
University degree (Postgraduate)	305(14.5)
Don't know/Refused/Other	162(7.7)
Personal Income (NZ$)	
Zero Income	110(5.2)
≤40,000	690(32.9)
40,001-60,000	343(16.4)
60,001-70,000	139(6.6)
70,001-100,000	221(10.5)
>100,000	213(10.2)
Don't know/Refused	381(18.2)
Household Income (NZ$)	
Zero Income	7(0.3)
≤40,000	341 (16.3)
40,001-60,000	194 (9.2)
60,001-70,000	102 (4.9)
70,001-100,000	263(12.5)
>100,000	593(28.3)
Don't know/Refused	599 (28.5)
Employment	
Employed	1402(66.8)
Unemployed, looking for work	94(4.5)
Unemployed, not looking for work (retired/caregiver/student etc.)	549(26.2)
Don't know/Other	52(2.5)
New Zealand Deprivation Index 2013	
Q1 (Less deprived)	520(24.8)
Q2	597(28.5)
Q3	474(22.6)
Q4	355(16.9)
Q5 (Most deprived)	151(7.2)

7.4.2 Descriptive characteristics of health-related variables by population socio-demographic elements

Over half of the study population was physically active on 5 or more days in the previous week (51.5%), and 55.4% were in the overweight/obese category (Table 42). Physical activity declined with increasing age, with the youngest age group being most active (54.1 %), while only 40.2% of the over 65 age group met the recommended daily activity guidelines. The youngest age group also had the lowest percentage of overweight/obesity levels (37.6%), which were over 20% higher for all other age groups. Males were more physically active than females (55.2% vs. 48.7%), but also had a higher percentage of overweight/obesity (62.2% in comparison to 50.3%). The Māori ethnic group had the highest percentage of individuals meet the physical activity guidelines (61.8%) in comparison to all other ethnicities, but also had a higher percentage of overweight and obese individuals (65.9%) than both Asian (46.6 %) and European/Other (54.5%) groups, but not for the Pacific ethnic group where overweight and obesity was higher (73.5%). There was little difference between the percentages of physically active and overweight/obese individuals who had few or many qualifications, one exception being those with a post high school diploma or trade certificate were less physically active (46.5%), with higher percentages of overweight/obesity (61.9%) than the rest of the study sample.

Interestingly, individuals with the highest household income had the highest percentage of overweight/obesity (60.4%) in comparison to all other income bands including the zero group with only 7 participants, where 28.6 % were overweight/obese. Those earning between NZ$40-60K were the most physically active (58.2%) and were also less overweight/obese in comparison to all other earners in the study population (56.7%). Over half of those employed were physically active (53.7%) but were also overweight/obese (58%). Individuals living in the least deprived areas were less physically active (43.5%) than those living in all other areas. Even though the percentages of individuals overweight or obese were over 50% across all deprivation quintiles, individuals living in quintile 4 and quintile 5 (the most deprived) were comparatively the most overweight/obese (59.4% and 57.6%, respectively). Whether or not individuals met the guidelines of 30 minutes of physical activity on 5 or more days did not have much influence on whether they were overweight/obese with only a 0.5% of a difference between the two groups (Table 42). Just over half of individuals (54.7%) with a BMI of less than 25 (normal weight) were physically active and similarly those with a BMI greater or equal to 25 (overweight/obese) only 51.3% were physically active (Table 42).

Table 42. Socio-demographic characteristics of NZHS study sample by health-related variables.

Variable	n	Physically Active %, (n missing)	Overweight/Obese %, (n missing)
Total population	2097	51.5 (9)	55.4 (175)
Age			
15-29	471	54.1 (5)	37.6 (31)
30-44	669	53.7 (1)	59.2 (60)
45-54	384	53.9 (2)	62.2 (24)
55-64	262	50.8 (0)	62.6 (22)
≥65	311	40.2 (0)	59.5 (38)
Sex			
Female	1198	48.7 (4)	50.3 (132)
Male	899	55.2 (4)	62.2 (43)
Ethnicity			
Māori	220	61.8 (1)	65.9 (14)
Pacific	83	55.4 (0)	73.5 (12)
Asian	294	43.9 (4)	46.6 (25)
European/Other	1500	51.2 (3)	54.5(124)
Qualification			
No high school qualification	495	50.7 (3)	53.5 (54)
High school qualification	208	51.4 (1)	56.3 (12)
Post-high school diploma or trade certificate	396	46.5 (0)	61.9 (31)
University degree (Undergraduate)	531	56.3 (4)	53.7 (37)
University degree (Postgraduate)	305	54.1 (0)	54.1 (21)
Don't know/Refused/Other	162	-	-
Household Income (NZ$)			
Zero	7	28.6 (0)	28.6 (2)
≤40,000	341	47.8 (1)	58.7(23)
40,001-60,000	194	58.2(0)	56.7 (12)
60,001-70,000	102	46.1 (0)	56.9 (5)
70,001-100,000	263	52.9 (0)	58.2 (21)
>100,000	593	55.8 (0)	60.4 (39)
Don't know/Refused	599	-	-
Employment			
Employed	1402	53.7 (5)	58.0 (107)
Unemployed, looking for work	94	46.8 (1)	57.4 (7)
Unemployed, not looking for work (retired/caregiver/student etc.)	549	46.1 (2)	49.5 (60)
Don't know/Other	52	-	-
New Zealand Deprivation Index 2013			
Q1 (Least deprived)	520	43.5 (1)	56.2 (46)
Q2	597	51.1 (5)	52.3 (59)
Q3	474	60.3 (1)	54.6 (32)
Q4	355	50.4 (0)	59.4 (22)
Q5 (Most deprived)	151	55.0 (1)	57.6 (16)

Table 42. Continued, percentage of physically active and overweight/obese individuals in the NZHS sample.

Variable	n	Physically Active %, (n missing)	Overweight/Obese %, (n missing)
Physically Active			
5 or more days of 30 minutes PA over a week	1079	100 (8)	55.2 (67)
Less than 5 days of 30 minutes of PA over a week	1010	0 (8)	55.7 (106)
Overweight/ Obese			
BMI<25 (Normal weight)	761	54.7(4)	0 (175)
BMI ≥25 (Overweight/Obese)	1161	51.3 (2)	100 (175)

7.4.3 Associations between walkability and physical activity

This section investigates associations between indices of walkability and physical activity using specific research questions to guide the analyses:

A) Do the odds of meeting the recommended physical activity guidelines increase as walkability of the built environment increases?

B) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results for Model 1

Results of the binomial generalised logistic regression analyses are presented through ORs and confidence intervals (Table 43). Overall, both the Basic Walk Indices (BWIs) and Enhanced Walk Indices (EWIs), (model 1, the bivariate analysis) across each of the methods for each spatial level had at least one- if not three- statistically significant relationships with physical activity behaviours. Specifically, the BWI method 1 (standard method, network buffer) and BWI method 3 (novel method, network buffer) were consistently statistically significant across all three spatial levels (800m, 1600m and 2400m). The significance level and ORs were higher for BWI method 3 in comparison to BWI method 1. This result indicates that an increase of one unit in the walkability of the built environment (based on BWI method 3) was related to an increased likelihood of meeting the physical activity guidelines by 16% ($p<0.001$). In comparison, the standard method of walkability (BWI method 1), reported a one unit increase in walkability was related to a 7% increase in the likelihood of meeting physical activity guidelines. In contrast to the BWIs, each of the EWIs were significantly related to physical activity for two out of the three spatial levels (800m and 1600m). ORs were slightly higher in comparison to the BWI methods. For example, a one unit increase in walkability based on the EWI method 3, (800m network defined neighbourhood) was associated with a 12% increased odds of meeting physical activity guidelines. These findings indicate that both the BWI and EWI, based on method 3, at the 800m spatial level are strong predictors of physical activity.

Examining the performance of the indices at the 1600m spatial level, all indices were statistically significant with p-values ranging in significance from $p<0.05$ to $p<0.001$, potentially indicating that 1600m is a useful distance, regardless the method or buffer type, for measuring associations between the walkability and physical activity. The results for method 2 (Euclidean buffer around PWCs) were significant at 1600m for BWI, and significant at 800m and 1600m for EWI. ORs were relatively similar to those for the BWI based on method 1 and comparatively lower than the other indices.

Results for Model 2

Results for model 2 (where all indices were adjusted for age, sex and ethnicity) were varied; however trends began to emerge for certain indices. The BWI based on method 1 only remained significant at 2400m spatial level and the odds ratio decreased by 2% after adjusting for covariates. Results for the semi-adjusted BWI based on method 2 reached significance at the 800m level, but failed to attain significance at 1600m and 2400m; whereas no significant association was found for EWI method 2 after adjusting for individual demographic covariates. The BWI based on method 3 retained significance at 800m and 1600m but not at the 2400m level. Similar to results from the unadjusted model, both the BWI and EWI, based on method 3, had the highest odds ratios at the 800m level. For example, after adjusting for age, sex and ethnicity, both the BWI and EWI (method 3) were associated with an increased likelihood of meeting physical activity guidelines (13% and 10% respectively).

Results for Model 3

The results for model 3, (where models were also adjusted for education, employment and household income), were relatively similar to model 2, with a few exceptions. The odds ratios for the BWI based on method 2, improved for the 800m level and reached significance at 1600m spatial level. Also, the results of the EWI based on method 2, did not reach significance at any level for model 2 but did become significant after additionally adjusting for education, employment and household income (model 3) at the 800m level.

Results for Model 4

Finally, there were no statistically significant associations evident in the fully adjusted model 4, after adding a measure for area deprivation. However, even though the indices did not reach statistical significance the trend across each of the indices at all spatial levels was in the expected direction, (i.e. greater than 1). This results suggests neighbourhood deprivation could be a potential mediator in the relationship between the built environment and physical activity behaviours.

Table 43. Unadjusted and covariate adjusted associations between the Basic Walk Indices and the Enhanced Walk Indices and physical activity behaviours (odds ratios, 95% confidence intervals and p-values reported).

Physical Activity

Variables	Model 1			Model 2			Model 3			Model 4		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
BWI Method 1												
800m	**1.06**	**1.01-1.11**	**<0.05**	1.04	0.99-1.09	0.08	1.05	0.99-1.10	0.07	1.01	0.96-1.07	0.70
1600m	**1.05**	**1.01-1.10**	**<0.05**	1.04	0.99-1.09	0.11	1.04	0.99-1.09	0.09	1.01	0.95-1.06	0.83
2400m	**1.07**	**1.02-1.11**	**<0.01**	**1.05**	**1.00-1.10**	**<0.05**	1.05	1.00-1.10	<0.05	1.03	0.98-1.08	0.31
BWI Method 2												
800m	1.09	1.03-1.16	1.16	**1.07**	**1.01-1.14**	**<0.05**	**1.08**	**1.01-1.14**	**<0.05**	1.05	0.98-1.12	0.19
1600m	**1.05**	**1.01-1.10**	**<0.05**	1.04	0.99-1.09	0.05	**1.04**	**1.00-1.09**	**<0.05**	1.02	0.98-1.07	0.35
2400m	1.03	0.99-1.06	0.19	1.02	0.98-1.06	0.34	1.02	0.98-1.06	0.30	1.00	0.96-1.04	0.98
BWI Method 3												
800m	**1.16**	**1.07-1.26**	**<0.001**	**1.13**	**1.04-1.23**	**<0.01**	**1.13**	**1.04-1.24**	**<0.01**	1.09	0.99-1.20	0.09
1600m	**1.10**	**1.03-1.17**	**<0.01**	**1.08**	**1.01-1.15**	**<0.05**	**1.09**	**1.02-1.16**	**<0.05**	1.06	0.99-1.14	0.10
2400m	**1.06**	**1.00-1.11**	**<0.05**	1.04	0.99-1.10	0.12	1.04	0.99-1.10	0.11	1.02	0.97-1.08	0.39
EWI Method 2												
800m	**1.09**	**1.02-1.17**	**<0.05**	1.07	0.99-1.15	0.05	**1.08**	**1.00-1.16**	**<0.05**	1.04	0.96-1.12	0.35
1600m	**1.06**	**1.01-1.11**	**<0.05**	1.05	0.99-1.10	0.08	1.05	0.99-1.10	0.07	1.02	0.97-1.08	0.39
2400m	1.03	0.99-1.08	0.16	1.02	0.98-1.07	0.31	1.02	0.98-1.07	0.27	1.00	0.96-1.05	0.86
EWI Method 3												
800m	**1.12**	**1.03-1.23**	**<0.05**	**1.10**	**1.00-1.20**	**<0.05**	**1.10**	**1.01-1.21**	**<0.05**	1.04	0.93-1.16	0.52
1600m	**1.08**	**1.00-1.17**	**<0.05**	1.07	0.99-1.15	0.10	1.07	0.99-1.16	0.08	1.03	0.95-1.12	0.46
2400m	1.07	0.99-1.16	0.08	1.05	0.97-1.14	0.20	1.06	0.97-1.14	0.19	1.02	0.94-1.11	0.68

Model 1, unadjusted bivariate regression; Model 2, adjusted for age, sex and ethnicity (individual level covariates); Model 3, additionally adjusted for education, employment, household income (individual level covariates); Model 4, additionally adjusted for NZ Deprivation (area level covariate).

7.4.4 Associations between walkability and overweight/obesity

This section investigates associations between indices of walkability and overweight/obesity using specific research questions to guide the analyses:

C) Do the odds of being overweight/obese decrease as walkability of the built environment increases?

D) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results for Model 1

Results of the negative binomial regression analyses are presented through ORs and confidence intervals and presented in Table 44. Overall, the results of the unadjusted model 1, reported significant associations between walkability and overweight/obesity, in the expected direction (i.e. less than 1.00), this was true for all indices, in at least one of the spatial levels (800m, 1600m or 2400m).

In comparison to all walk indices (BWI, EWI based on methods 2 and 3), the BWI based on method 1, (standard method) was only significant at 2400m (OR 0.94). Additionally, the BWI based on method 2 was the only BWI to attain significance across all three spatial levels (800m, 1600m and 2400m), and was significantly negatively associated with overweight/obesity. However, the effect sizes were smaller than the other methods. The BWI based on method 3 had higher ORs for both 1600m and 2400m, than the other BWI methods (OR0.90 and OR0.91, respectively). This suggests that for every unit increase in the walkability (BWI, method 3, 1600m) of the built environment, the likelihood of being overweight or obese was associated with a decrease of 10% ($p<0.01$).

In comparison to the BWIs, each of the EWIs (methods 2 and 3) achieved statistically significant lower ORs for the 1600m and 2400m spatial levels. Method 3, again, had similar ORs for the EWIs, where a unit increase in the walkability of the built environment was associated with a 12% decreased odds of being overweight or obese.

Results for Models 2 and 3

After adjusting for socio-demographic covariates in models 2 and 3, all indices, except the BWI and EWI, based on method 3, failed to reach significant associations. However, all other indices at all spatial levels continued to show the trend that as walkability increased the likelihood of being overweight/ obese decreased. In the cases of the BWI and EWI based on method 3, both indices retained significance at $p<0.05$ and the ORs marginally worsened from model 1 (OR 0.92, 1600m and OR 0.93, 2400m).

Results for Model 4

Finally, after adjusting for area deprivation, all indices with significant results for model 1 were significant again for model 4. Importantly, in comparison to all other indices, both the BWI and the EWI based on method 3 remained consistently significant at 1600m and 2400m after adjusting for each group of covariates (models 1-4). Furthermore, the ORs continued to improve across each of the models with the fully adjusted models having the lowest values. Comparing between the BWIs and EWIs, the EWIs overall, performed better. The EWI based on method 3 achieved an OR of 0.87, ($p<0.01$) at 1600m and an OR of 0.88, ($p<0.01$) at 2400m.

Table 44. Unadjusted and covariate adjusted associations between the Basic Walk Indices and the Enhanced Walk Indices and overweight/obesity (BMI≥25, odds ratios, 95% confidence intervals and p-values reported).

Overweight/Obese (BMI ≥25)

Variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
BWI Method 1												
800m	0.97	0.93-1.02	0.31	0.99	0.94-1.04	0.73	0.99	0.94-1.05	0.85	0.96	0.91-1.02	0.22
1600m	0.97	0.92-1.02	0.18	0.98	0.93-1.03	0.41	0.98	0.93-1.03	0.49	0.95	0.89-1.00	0.07
2400m	**0.94**	**0.90-0.99**	**<0.05**	0.96	0.91-1.00	0.07	0.96	0.91-1.01	0.08	**0.93**	**0.88-0.98**	**<0.01**
BWI Method 2												
800m	**0.94**	**0.88-0.99**	**<0.05**	0.96	0.89-1.02	0.18	0.97	0.91-1.03	0.33	0.93	0.86-1.00	0.06
1600m	**0.95**	**0.91-0.99**	**<0.05**	0.96	0.92-1.01	0.12	0.97	0.92-1.01	0.17	**0.94**	**0.90-0.99**	**<0.05**
2400m	**0.95**	**0.92-0.99**	**<0.05**	0.97	0.93-1.01	0.12	0.97	0.93-1.01	0.20	**0.95**	**0.91-0.99**	**<0.05**
BWI Method 3												
800m	0.92	0.84-1.00	0.06	0.95	0.87-1.04	0.29	0.97	0.88-1.06	0.45	0.90	0.81-1.01	0.07
1600m	**0.90**	**0.83-0.96**	**<0.01**	**0.92**	**0.85-0.98**	**<0.05**	**0.93**	**0.86-0.99**	**<0.05**	**0.90**	**0.83-0.97**	**<0.01**
2400m	**0.91**	**0.86-0.97**	**<0.01**	**0.93**	**0.88-0.99**	**<0.05**	**0.94**	**0.88-0.99**	**<0.05**	**0.92**	**0.86-0.98**	**<0.01**
EWI Method 2												
800m	0.94	0.87-1.01	0.09	0.96	0.89-1.03	0.26	0.97	0.90-1.05	0.42	0.93	0.85-1.01	0.09
1600m	**0.93**	**0.89-0.99**	**<0.05**	0.95	0.90-1.00	0.05	0.95	0.90-1.01	0.09	**0.93**	**0.87-0.98**	**<0.05**
2400m	**0.94**	**0.90-0.99**	**<0.05**	0.96	0.91-1.00	0.08	0.96	0.92-1.01	0.14	**0.95**	**0.90-0.99**	**<0.05**
EWI Method 3												
800m	0.91	0.83-1.00	0.06	0.94	0.85-1.04	0.24	0.96	0.86-1.06	0.37	**0.88**	**0.77-0.99**	**<0.05**
1600m	**0.88**	**0.81-0.96**	**<0.01**	**0.90**	**0.83-0.99**	**<0.05**	**0.91**	**0.84-0.99**	**<0.05**	**0.87**	**0.78-0.96**	**<0.01**
2400m	**0.88**	**0.81-0.96**	**<0.05**	**0.91**	**0.83-0.99**	**<0.05**	**0.91**	**0.83-0.99**	**<0.05**	**0.88**	**0.80-0.96**	**<0.01**

Model 1, unadjusted bivariate regression; Model 2, adjusted for age, sex and ethnicity (individual level covariates); Model 3, additionally adjusted for education, employment, household income (individual level covariates); Model 4, additionally adjusted for NZ Deprivation (area level covariate).

7.4.5 Associations between bikeability and physical activity

This section investigates associations between indices of bikeability and physical activity using specific research questions to guide the analyses:

E) Do the odds of meeting the recommended physical activity guidelines increase as bikeability of the built environment increases?

F) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results for Model 1

Results based on ORs and confidence intervals and presented in Table 45. Results of the bivariate analyses for both methods (Bike Index, based on methods 2 and 3) were similar for 800m and 1600m, ORs were close to 1.00 but did have a statistically significant association. The BI based on method 3 was the only method to have a significant association with physical activity behaviours for the three spatial levels (800m, 1600m and 2400m), however the small effect sizes were relatively small.

Results for Models 2 and 3

After adjusting for sex, ethnicity and age in model 2, BI method 2 failed to reach significance across any of the spatial levels. The BI based on method 3, however, remained significant for 800m and 1600m, again the ORs were low, as bikeability increased, the likelihood of meeting physical activity guidelines increased by 2% at 1600m scale. The results for model 3, were largely unchanged after also adjusting for education, employment status and household income, indicating that these covariates do not have a significant influence on the overall relationship between bikeability and physical activity.

Results for Model 4

In the fully adjusted model, 4, there were no significant associations found between physical activity and the indices for bikeability across any spatial level. The attenuation of a relationship for all methods, especially method 3, indicate that neighbourhood deprivation has a strong influence on physical activity behaviours.

Table 45. Unadjusted and covariate adjusted associations between Bike Indices and physical activity behaviours (odds ratios, 95% confidence intervals and p-values reported).

Physical activity

Variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
Bike Index Method 2												
800m	**1.00**	**1.00-1.01**	**<0.05**	1.01	1.00-1.03	0.14	1.01	0.99-1.03	0.14	1.00	0.98-1.02	0.71
1600m	**1.00**	**1.00-1.01**	**<0.05**	1.01	0.99-1.03	0.13	1.01	0.99-1.03	0.14	1.01	0.99-1.03	0.57
2400m	1.00	0.99-1.00	0.68	1.00	0.98-1.01	0.87	0.99	0.98-1.01	0.83	0.99	0.98-1.01	0.34
Bike Index Method 3												
800m	**1.00**	**1.00-1.01**	**<0.05**	**1.01**	**1.00-1.03**	**<0.05**	**1.02**	**1.00-1.03**	**<0.05**	1.01	0.99-1.03	0.28
1600m	**1.01**	**1.00-1.01**	**<0.01**	**1.02**	**1.00-1.04**	**<0.05**	**1.02**	**1.00-1.04**	**<0.05**	1.02	0.99-1.04	0.11
2400m	**1.01**	**1.00-1.01**	**<0.05**	1.02	0.99-1.04	0.05	1.02	0.99-1.04	0.06	1.01	0.98-1.04	0.45

Model 1, unadjusted bivariate regression
Model 2, adjusted for age, sex and ethnicity (individual level covariates)
Model 3, additionally adjusted for education, employment, household income (individual level covariates)
Model 4, additionally adjusted for NZ Deprivation (area level covariate).

7.4.6 Associations between bikeability and overweight/obesity

This section investigates associations between indices of bikeability and overweight/obesity health outcomes using specific research questions to guide the analyses:

G) Do the odds of being overweight/obese decrease as bikeability of the built environment increases?

H) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results of the negative binomial regression analyses are presented through ORs and confidence intervals and presented in Table 46. Associations trend in the expected direction, (i.e. less than 1.00).

Results for Model 1

In the unadjusted bivariate analysis (model 1), the BI based on method 2 for 1600m and 2400m had the same ORs (0.98) and significance level ($p<0.05$). The BI based on method 3 found for every unit increase in bikeability at the 2400m spatial level, there was a 3% decrease in the likelihood of being overweight or obese ($p<0.05$).

Results for Models 2 and 3

However, in models 2 and 3 after adjusting for covariates, no association was found across each of the methods and spatial levels. The general trend of odds ratios being less than 1.00 remained. The attenuation of association after adding socio-demographic variables indicates the presence of confounding.

Results for Model 4

The results across all indices and spatial levels after adjusting for neighbourhood deprivation were extraordinarily improved, with significance of $p<0.01$ reached for all methods except in method 3 at 2400m achieving $p<0.001$. This meant that as the bikeability of the neighbourhood at 2400m increased, the likelihood of being overweight or obese decreased by 5 %.

Table 46. Unadjusted and covariate adjusted associations between Bike Indices and overweight/obesity (BMI ≥25, odds ratios, 95% confidence intervals and p-values reported).

Overweight/Obese (BMI ≥25)

Variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
Bike Index Method 2												
800m	0.98	0.97-1.00	0.06	0.99	0.98-1.01	0.41	0.99	0.98-1.01	0.41	**0.97**	**0.95-0.99**	**<0.01**
1600m	**0.98**	**0.96-0.99**	**<0.05**	0.99	0.97-1.01	0.16	0.99	0.97-1.00	0.14	**0.97**	**0.95-0.99**	**<0.01**
2400m	**0.98**	**0.97-0.99**	**<0.05**	0.99	0.97-1.00	0.10	0.99	0.97-1.00	0.08	**0.97**	**0.96-0.99**	**<0.01**
Bike Index Method 3												
800m	0.99	0.97-1.00	0.09	0.99	0.98-1.01	0.47	0.99	0.98-1.01	0.50	**0.97**	**0.96-0.99**	**<0.01**
1600m	**0.98**	**0.96-0.99**	**<0.05**	0.99	0.97-1.01	0.35	0.99	0.97-1.01	0.35	**0.97**	**0.95-0.99**	**<0.01**
2400m	**0.97**	**0.95-0.99**	**<0.05**	0.98	0.96-1.01	0.16	0.98	0.96-1.01	0.14	**0.95**	**0.93-0.98**	**<0.001**

Model 1, unadjusted bivariate regression
Model 2, adjusted for age, sex and ethnicity (individual level covariates)
Model 3, additionally adjusted for education, employment, household income (individual level covariates)
Model 4, additionally adjusted for NZ Deprivation (area level covariate).

7.4.7 Associations between neighbourhood destination accessibility and physical activity

This section investigates associations between indices of neighbourhood destination accessibility and physical activity using specific research questions to guide the analyses:

I) Do the odds of meeting the recommended physical activity guidelines increase as neighbourhood destination accessibility of the built environment increases?

J) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results for Model 1

Similar to previous sections, results of the negative binomial regression are presented through ORs and confidence intervals and shown in Table 47. Accessibility to neighbourhood destinations was significantly associated with physical activity in all methods and spatial levels. However, effect sizes, reported in ORs, were small (~1-2%).

Results for Models 2 and 3

After adjusting for socio-demographic covariates, the NDAI based on method 2 were significantly associated with physical activity at both 800m and 1600m. The relationship between the NDAI based on method 3 and physical activity behaviours was significant across all three spatial levels, 800m, 1600m and 2400m. Again, the effect sizes were small, (~1-2%).

Results for Model 4

In the fully adjusted model, the NDAI based on method 2 remained significant for 800m and 1600m spatial levels only. Even though statistical significance was found between both methods 2 and 3 and physical activity, the effect sizes were small, (OR 1.01, CI, 1.00-1.02).

Table 47. Unadjusted and covariate adjusted associations between Neighbourhood Destination Accessibility Indices and physical activity behaviours (odds ratios, 95% confidence intervals and p-values reported).

Physical activity

Variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
NDAI Method 2												
800m	**1.01**	**1.01-1.02**	**<0.001**	**1.01**	**1.00-1.02**	**<0.01**	**1.01**	**1.00-1.02**	**<0.01**	**1.01**	**1.00-1.02**	**<0.05**
1600m	**1.01**	**1.01-1.02**	**<0.001**	**1.01**	**1.01-1.02**	**<0.001**	**1.01**	**1.01-1.02**	**<0.001**	**1.01**	**1.00-1.02**	**<0.01**
2400m	1.01	0.99-1.01	0.09	1.00	1.00-1.01	0.27	1.00	0.99-1.01	0.29	1.00	0.99-1.01	0.65
NDAI Method 3												
800m	**1.01**	**1.00-1.02**	**<0.01**	**1.01**	**1.00-1.02**	**<0.01**	**1.01**	**1.00-1.02**	**<0.01**	1.01	0.99-1.01	0.07
1600m	**1.02**	**1.01-1.02**	**<0.001**	**1.01**	**1.01-1.02**	**<0.01**	**1.01**	**1.01-1.02**	**<0.01**	**1.01**	**1.00-1.02**	**<0.05**
2400m	**1.02**	**1.01-1.03**	**<0.001**	**1.02**	**1.01-1.03**	**<0.001**	**1.02**	**1.01-1.03**	**<0.001**	**1.01**	**1.00-1.02**	**<0.05**

Model 1, unadjusted bivariate regression
Model 2, adjusted for age, sex and ethnicity (individual level covariates)
Model 3, additionally adjusted for education, employment, household income (individual level covariates)
Model 4, additionally adjusted for NZ Deprivation (area level covariates).

7.4.8 Associations between neighbourhood destination accessibility and overweight/obesity

This section investigates associations between indices of neighbourhood destination accessibility and overweight/obesity using specific research questions to guide the analyses:

A) Do the odds of being overweight/obese decrease as neighbourhood destination accessibility of the built environment increases?

B) How do results vary depending on 1) buffer delineation and 2) spatial scale, after controlling for potential confounders?

Results for Model 1

The results of the negative binomial regression analyses are presented through ORs and confidence intervals and shown in Table 48. In general, significant associations were found between the exposures of interest (the NDAIs) and overweight/obesity for all methods and spatial scales. Even though significance was evident for both methods 2 and 3, the effect sizes were small, (OR 0.98 and OR 0.99).

Results for Models 2 and 3

After adjusting for socio-demographic covariates in model 2 and 3, NDAIs based on methods 2 and 3 remained significantly associated with a decreased odds of being overweight or obese at 2400m spatial level only. The addition of covariates reduced the significance of results, however there was still a consistent trend with all ORs below 1.00.

Results for Model 4

In the final set of analyses, after adjusting for neighbourhood deprivation, associations between the NDAIs based on methods 2 and 3, remained at the 2400m level but also reached statistical significance at $p<0.01$ for the 800m and 1600m spatial levels. These results suggest that neighbourhood deprivation is significant confounder and has potentially a strong mediating effect on the relationship between the neighbourhood destination accessibility and overweight/obesity.

Table 48. Unadjusted and covariate adjusted associations between Neighbourhood Destination Accessibility Indices and overweight/obesity (BMI ≥25, odds ratios, 95% confidence intervals and p-values reported).

Overweight/Obese (BMI ≥25)

Variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**		
	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value	OR	CI (95%)	P-value
NDAI Method 2												
800m	**0.99**	**0.98-0.99**	**<0.05**	0.99	0.99-1.00	0.23	0.99	0.99-1.00	0.25	**0.99**	**0.98-0.99**	**<0.01**
1600m	**0.99**	**0.98-0.99**	**<0.05**	0.99	0.99-1.00	0.09	0.99	0.99-1.00	0.09	**0.99**	**0.98-0.99**	**<0.01**
2400m	**0.99**	**0.98-0.99**	**<0.001**	**0.99**	**0.98-0.99**	**<0.01**	**0.99**	**0.98-0.99**	**<0.01**	**0.98**	**0.98-0.99**	**<0.001**
NDAI Method 3												
800m	**0.99**	**0.98-0.99**	**<0.01**	0.99	0.99-1.00	0.12	0.99	0.99-1.00	0.13	**0.99**	**0.98-0.99**	**<0.01**
1600m	**0.99**	**0.98-0.99**	**<0.01**	0.99	0.98-1.00	0.20	0.99	0.98-1.00	0.22	**0.98**	**0.97-0.99**	**<0.01**
2400m	**0.98**	**0.97-0.99**	**<0.001**	**0.99**	**0.98-1.00**	**<0.05**	**0.99**	**0.98-1.00**	**<0.05**	**0.98**	**0.96-0.99**	**<0.001**

Model 1, unadjusted bivariate regression
Model 2, adjusted for age, sex and ethnicity (individual level covariates)
Model 3, additionally adjusted for education, employment, household income (individual level covariates)
Model 4, additionally adjusted for NZ Deprivation (area level covariates).

7.5 Summary of findings

Walk Indices

The walkability of the built environment was associated with an increased likelihood of physical activity for the BWIs based on methods 1 and 3 across all spatial scales and 1600m only for the BWI based on method 2. Small but statistically significant bivariate associations were found for most of the BWI and EWI based methods. When comparing the results of the novel methods (2 and 3) against the standard method (BWI method 1), BWI (method 3) was significantly positively associated with physical activity across all spatial levels and had higher ORs and significance levels than the standard BWI based on method 1. Furthermore, both methods 1 and 3 are based on network buffers, making their results comparable. Significant associations were also found for two out of the three (800m and 1600m) spatial scales for each of the EWIs. In general, the strength of effect was similar to the BWIs. The 1600m spatial level emerged as the only scale, regardless of method and buffer choice, to show a consistent pattern of association between walkability and physical activity behaviours.

On the whole, independent of demographic and socio-economic covariates, the BWI based methods, for at least one scale, retained higher ORs of associations with physical activity, than the EWIs, (methods 2 and 3). In the fully adjusted model, all indices failed to reach statistical significance. The addition of neighbourhood deprivation attenuated the strength of association, indicating a strong negative confounding with physical activity.

The likelihood of being overweight or obese was significantly lower in walkable neighbourhoods, this was true for all methods and at least one spatial scale (2400m) in the unadjusted analyses. The network based buffer, (method 3), for both the BWI and EWI, were the only indices to remain statistically significant after adjusting for all socio-demographic covariates. Furthermore, after adjusting for neighbourhood deprivation the odds ORs improved, with EWI based on method 3 reporting a 13% decreased likelihood of individuals being overweight or obese in walkable neighbourhoods at the 1600m scale. This finding lends further evidence that 1600m is an appropriate scale for investigating relationships between walkability and overweight/obese.

Bike Indices

Bikeability was significantly associated with meeting physical activity guidelines in the unadjusted bivariate model for the BI based on method 2 (800m, 1600m) and BI based on method 3 (800m, 1600m and 2400m). Significant positive associations remained for method 3 (network buffer) after adjusting for both demographic and socio-economic covariates. Effect sizes were small, where a unit increase in the bikeability of the built environment was associated with a 1-2% increased odds of meeting physical activity guidelines. Similar to the walkability indices, no significant relationship existed after adjusting for neighbourhood deprivation, indicating a strong confounding relationship with physical activity.

The bikeability of the built environment was significantly positively associated with reduced odds of being overweight or obese. This was true for each method at 1600m and 2400m scales in the unadjusted model. No significant relationship was found between bikeability and overweight/obesity after adjusting for potential demographic and socio-economic confounders. However, after including neighbourhood deprivation in the fully adjusted model, all methods, across all spatial scales were significantly associated with overweight/ obesity health outcomes. This result suggests neighbourhood deprivation potentially influences the relationship between bikeability of the built environment and overweight/obesity. The BI based on method 3, (network buffer) at 2400m, reported the lowest ORs in comparison to all other methods and scales. The likelihood of being overweight or obese was 5% lower in more bikeable neighbourhoods, based on the method 3 definition.

Neighbourhood Destination Accessibility Indices

Neighbourhood destination accessibility was significantly positively associated with physical activity for method 2 at 800m and 1600m and method 3 across all three spatial levels. Effect sizes remained small after adjusting for demographic and socio-economic covariates, where a unit increase in neighbourhood destination accessibility was associated with a 1-2% increase in physical activity, (method 2, 800m and 1600m; method 3, all three levels). The NDAIs based on methods 2 and 3, (Euclidean and network buffers) remained significantly associated with physical activity even after adjusting for neighbourhood deprivation. Due to the marginal effect sizes between the methods, it is difficult to determine or recommend which method is better at predicting associations with physical activity. Further research is required.

An increase in destination accessibility was significantly associated with a lower likelihood of being overweight/obese for all methods and spatial scales in the unadjusted model. This finding remained at the 2400m scale after adjusting for potential demographic and socio-economic confounders. In the fully adjusted model, including neighbourhood deprivation, all methods at all spatial scales were statistically significant, even though the effect sizes were small. Importantly, effect sizes were in the expected direction, this finding suggests that increasing accessibility of destinations in the neighbourhood environment within a 10-30 minute walk could improve health-related outcomes.

Chapter Conclusion

This chapter examined the results of associations between indices of the built environment, physical activity behaviours and health outcomes. Results indicate that the novel EWI based on method 3 (KDE values averaged to the network buffer) is a better measure of walkability than the novel BWI method 3. In addition, the novel BWI method 3 was a better measure than the BWI based on the standard method 1 (network buffer) especially for overweight/obesity. This indicates that both the novel method and the additional features added to the EWI are a strong improvement on the standard method and BWI (method 1). Further, significant negative associations existed between the indices of bikeability (methods 2 and 3) and overweight/obesity, where an increase in bikeability of the built environment was inversely associated with BMI. Indices of neighbourhood destination accessibility was also significantly positively associated with meeting physical guidelines and reduced odds of being overweight/obese. Choice of scale and method influenced whether associations achieved significance. In addition, area deprivation had a strong confounding effect on the relationship between physical activity and the walkability and bikeability of the built environment. Further investigation and discussion of the main findings arising from these analyses are presented in the following chapter, (Chapter 8).

Chapter 8. Discussion and conclusions

This thesis research has made a number of important methodological contributions and advancements to the field of research on the built environment, active transport, physical activity and health outcomes. The overall aims of this research were 1) to develop novel objective measures of the built environment for walking, cycling and neighbourhood destination accessibility; and 2) to comprehensively test associations between the novel indices and active transport, physical activity behaviours and health outcomes, using available secondary data. These aims were achieved by meeting a series of research objectives (presented in Chapters 3-7) and addressing specific research questions (Chapters 5-7). The next paragraph gives a brief reminder of the context of the study area. The remainder of the chapter will: discuss the main research findings, referring to different chapters in this thesis (Section 8.1); give an overview of the challenges and opportunities in measuring the built environment for active transport and physical activity (Section 8.2); discuss the methodological contributions (Section 8.3), limitations and strengths of this research (Section 8.4); discuss implications of this research (Section 8.5) and future research directions into the built environment, active transport and physical activity behaviours (Section 8.6). Finally, a brief conclusion of this thesis research is provided (Section 8.7).

Wellington City was selected to test the standard and novel objective measures of the built environment for a number of reasons. Firstly, the terrain is mountainous around the fringe and relatively flat in the city centre, which is different to other larger New Zealand cities, and of interest to study because the presence of hills can affect active transport and physical activity behaviours. Second, the city has the highest employment density and the highest proportion of active transport commuters in New Zealand (Statistics New Zealand, 2015b). Third, previous research by Mavoa et al., (2009) has found Wellington City to have higher walkability scores, partially due to its more compact urban design, than three other cities in New Zealand; Christchurch, North Shore and Waitakere (the latter two were incorporated into Auckland City in 2010, New Zealand's largest city). Replicating methodologies and comparing findings with previous research in New Zealand is important for assessing the reliability and validity of previous research (Brownson et al., 2009) and contributing to the research field.

8.1 Discussion of findings

This section briefly discusses the gaps and motivations underpinning this thesis research. A discussion follows, describing the main research findings along with the outcomes and their implications, while addressing the main research objectives. Following the structure of the thesis, the findings are presented per chapter.

Chapter 2 provided an overview of the evidence linking the built environment, active transport, physical activity and overweight/obesity, addressing the first research objective. The socio-ecological model (Sallis et al., 2012) is regularly used to understand the multiple factors influencing physical activity behaviours. This study supports this thesis research in providing a model for the analysis of confounding factors influencing the relationships between the built environment, active transport and physical activity behaviours. The frameworks developed by Handy et al., (2002) and Pikora et al., (2003), formed a basis from which to work by identifying particular features of the built environment that can influence active transport, physical activity behaviours and health outcomes.

In order to meet the second research objective, Chapter 2 also provided a review of the literature used to objectively define the neighbourhood environment for walking and cycling. Specifically, the standard walk index, based on methods developed by Frank et al., (2005) and replicated by Leslie et al., (2007) and Mavoa et al., (2009), were reviewed. Limitations of this standard method were identified, including the use of vector based polygons to represent administratively defined ‘neighbourhoods’ based on the meshblock, which can be ambiguous and arbitrarily defined (Brownson et al., 2009; King et al., 2015). These limitations led to the exploration of an alternative, novel method, kernel density estimation (KDE), to measure the built environment for active transport, physical activity and health outcomes. KDE measures urban design features at a much finer resolution. For example, this research created a continuous surface of urban features using 10m x 10m raster cells. While previous studies have used KDE to measure crime hotspots (Chainey, 2013; Hart and Zandbergen, 2014), food outlets (Thornton et al., 2012; Rundle et al., 2009; Bader et al., 2010), and less commonly greenspace and recreation (Maroko, 2009), recreational resources (Diez-Roux et al., 2007) and neighbourhood destinations (King et al., 2015), only recent research by Buck et al., (2015a; 2015b) in Germany has used KDE to measure associations between the built environment and physical activity in children. To the author’s knowledge, this is the first published study to create features of the built environment using a novel (KDE) approach and investigate associations between these features and active transport, physical activity and overweight/obesity in adults.

The literature review also highlighted that objectively measuring the built environment for cycling was a relatively new concept, arising since 2010, in the literature. It is important to investigate features of the built environment that can influence cyclists separately, as factors that influence cycling behaviours can differ to walking behaviours (Wahlgren and Schantz, 2011; Winters et al., 2011). For example, cyclists potentially navigate the built environment differently to walkers due to topography and street connectivity (Berrigan et al., 2015). However, indices of bikeability are limited. Previous work by Winters et al., (2010) was the first to objectively measure the built environment for cycling in Toronto, Canada. To the author's knowledge, the built environment in New Zealand had not, prior to this thesis, been objectively measured for cycling and associations tested with active transport, physical activity and health outcomes. Furthermore, in relation to measures of destination accessibility, previous research in New Zealand (Witten et al., 2011) created a neighbourhood destination accessibility index (NDAI). Similar to the standard walk index, the standard NDAI was based on a simple intensity method. This approach has the same limitations as the standard walk index, whereby the proximity and density of destinations in relation to each other are not accounted for and equal exposure and accessibility to destinations is assumed across the areal unit or buffer. Similar to the bike index, the NDAI based on the novel approach has not, previous to this research, been tested in a New Zealand context.

These limitations and gaps in the literature motivated developing and testing standard and novel methods in this thesis in order to contribute to and progress methods used to measure the built environment in relation to active transport and health-related behaviours.

Further, relevant literature on objectively measured attributes and indices of the built environment for active transport and health were examined. Attributes such as land use mix, street connectivity, dwelling density and retail floor area are regularly associated with walking and physical activity (Brownson et al., 2009; Frank et al., 2010; Witten et al., 2012). In addition, these attributes are regularly combined into a composite index of walkability, using the standard method previously described, to predict walking behaviours (Frank et al., 2005; Frank et al., 2010; Brownson et al., 2009; Mavoa et al., 2009; Mayne et al., 2013). Moreover, other features such as slope, street lights, footpaths and tracks, bike rack density and length of cycle lanes are less commonly included in objective measures of the built environment even though they could potentially influence physical activity behaviours (Brownson et al., 2009; Winters et al., 2010). These features were included in the indices developed as part of this thesis research.

To address the third research objective, issues of scale and delineation in current literature were also investigated (Chapter 2). Buffers around individuals' home neighbourhood have previously been used as a way to manage the 'modifiable area unit problem' (Brownson et al., 2009). However, the type of buffer (Euclidean or network) used to 'capture' the exposure to features of the built environment and the appropriate scale in which to do so is still an area of debate (Oliver et al., 2007; Brownson et al., 2009). This research addressed these issues by analysing both Euclidean and network buffers at a range of scales, 800m, 1600m and 2400m.

The findings from this literature review formed the theoretical justification for investigating the commonly utilised walk index and developing an alternative method for measuring the built environment (KDE), including concepts of neighbourhood based on different delineations and spatial scales. In addition, the review helped identify the limited amount of research on measuring the bikeability of the built environment.

In order to address the fourth and fifth research objectives, standard (simple intensity) and novel (KDE) methods were used to create objective measures of the built environment, both individual (land use mix, dwelling density, street connectivity, slope, street lights, footpaths and tracks) and composite indices (Basic Walk Indices, Enhanced Walk Indices, Bike Indices, Neighbourhood Destination Accessibility Indices) (Chapter 3). In order to test the validity of the standard walkability index and to compare results with an alternate and novel method for measuring the built environment, two versions of the basic walk index (BWI) were created using measures of land use mix, street connectivity and dwelling density. The first BWI was based on the standard method (simple intensity) and the second BWI was based on the novel method (KDE with a vector component-buffers), an under-researched method in measuring the built environment for active transport and physical activity. Both BWIs comprised measures of land use mix, street connectivity and dwelling density. In addition, an enhanced walk index (EWI), based on the novel method was created in order to advance and address some of the limitations of the standard BWI. The EWI had three additional built environmental components including, slope, street lights and footpaths and tracks. Creating an alternative and novel BWI and EWI to the standard BWI was important in order to identify the similarities and differences between these methods and to investigate associations with active transport behaviours and health outcomes using available secondary data.

To address the sixth research objective, composite indices of bikeability (BI) using the novel method were created to test associations between active transport behaviours, physical activity behaviours and health outcomes, not previously completed in a New Zealand context (Chapter 3). Furthermore, an alternate version of Witten et al.,'s (2011) NDAI was developed using the novel method. Each of the EWIs, BIs and NDAIs were created using the novel method together with two methods of neighbourhood delineation, Euclidean and network buffer, and at a range of spatial scales.

In order to meet the seventh research objective, the spatial variations and data distributions of each of the indices and methods, based on both the Euclidean and network buffers at multiple spatial scales (800m, 1600m and 2400m), were investigated (Chapter 4). A combination of maps and histograms of the underlying data distribution of each of the indices was provided in order to identify the differences and similarities between the indices. Spatial distribution maps of methods 1, 2 and 3 used to create the BWIs and maps of methods 2 and 3 used to create the EWI, BI and NDAIs were compared and contrasted at three scales, 800m, 1600m and 2400m. The results of this investigation revealed variations in the underlying data between all four methods and across each spatial scale. Similar to previous research by Mavoa et al., (2009), high walkability for both the BWI and EWI were concentrated in the city centre. Furthermore, the addition of extra features in the EWI had similar patterns of high walkability to the BWI, however a greater area to the west of Wellington City was identified as having low walkability in the EWI. Similar to the walk indices, high bikeability and high destination accessibility were concentrated in the city centre. Chapter 4 served as a useful foundation to help visualise differences in each method, buffer type and spatial scale for the walk, bike and destination accessibility indices. In addition, using maps to identify areas of high/low walkability, bikeability and neighbourhood destination accessibility can help in communicating findings to health policy makers and urban planners.

To address the eighth research objective, the sensitivity of individual attributes and composite indices (BWI, EWI based on the novel methods) of the built environment were analysed with respect to individual travel data from the Household Travel Survey (Chapter 5). This chapter served as an exploratory pilot analysis of both the individual measures and composite indices of the built environment with self-reported individual level data on time spent walking. The chapter presented associations between time spent walking and individual and composite indices of the built environment in the home and destination environments at a range of spatial levels, 400m, 800m, 1200m, 1600m, 2000m and 2400m, and additionally along the route between home and destination using 50m and 100m buffers. Two outcome variables were utilised, walking up to 10 minutes and total time spent walking (up to 60 minutes). Findings for the individual and composite measures revealed a variation in associations with time spent walking, depending on the type of neighbourhood delineation and spatial scale used for the home, destination and route environments. Similar to previous research, (Badland et al., 2014; Mackenbach et al., 2016), the environments at the start (home) and end (destination) of a trip were important for predicting active transport behaviours. The main findings are briefly discussed below; both outcomes are discussed starting with the home environment, followed by the destination and route environments.

In the home environment based on the Euclidean buffer, independent of demographic, socio-economic and area deprivation, low density of slope within 1600m and high walkability (EWI) within 400m of the neighbourhood were significantly associated with walking up to 10 minutes. Comparing with the network buffer around the home, high dwelling density within 800m, low slope within 400m and high walkability within 400m and 800m of the home, were associated with higher likelihood of walking up to 10 minutes. These results show differences between both delineations and spatial scales around the home environment for slope and also that high walkability based on the EWI was a strong predictor of walking up to 10 minutes, with similar results for both delineations.

In contrast to short walking trips, low slope density around the home based on the Euclidean buffer at 2000m and 2400m, was negatively associated with longer time spent walking (Chapter 5). This finding could indicate that the low slope around the home is an important predictor of short walking trips but not necessarily for trips longer than 10 minutes. This finding is interesting and adds to the evidence base on slope and the relationship with walking, because few studies include this measure with active transport behaviours and health outcomes. It is especially important to test the influence of slope in environments that are mountainous such as Wellington City. Future research is necessary to assess the effects of slope in both flat and mountainous urban environments.

In addition, high land use mix around the home environment, both Euclidean (1600m, 2000m and 2400m) and network (2400m) buffers, was associated with longer time spent walking to any destination. These findings are in line with previous research in New Zealand, which found land use mix was associated with walking for all purposes, transport and leisure (Witten et al., 2012). Furthermore, this thesis research had similar findings to Mackenbach et al., (2016) who also found high land use mix around the home environment was associated with longer walking trips, based on self-report data from the same survey utilised in this research (New Zealand Household Travel Survey). Taken together, these findings lend validity to using land use mix as a measure to predict walking in the home environment. Living in neighbourhoods with a high mix of land uses within a 10-20 minute walk can encourage more time spent walking.

Of note, independent of demographic, socio-economic and area deprivation parameters, many of the individual and composite measures around the destination environments, based on the Euclidean buffer were associated with short walking trips. Specifically, dwelling density, street lights, footpaths and tracks, walkability based on the EWI and destination accessibility (NDAI) was all positively associated with short walking trips at various scales ranging from 400m to 1200m. In contrast, land use mix was negatively associated with short walking trips at the 800m neighbourhood level. Further research is needed to clarify associations between features of the destination environment and direct or multi walking trips to work and any destination.

In relation to longer walking trips, land use mix and walkability, (BWI), around the destination environment, based on the Euclidean buffer, were positively associated with total time spent walking. However, low slope density around the destination environment at 2000m and 24000m was negatively associated with longer walking trips. Based on the network buffer around the destination environment, only dwelling density was positively associated with short walking trips. In addition, only land use mix and walkability based on the BWI, were positively associated longer walking trips. Previous research by Mackenbach et al., (2016) did not report findings on longer walking trips and the environment around destinations, therefore no comparisons with existing research can be completed.

Independent of demographic, socio-economic and area deprivation elements, no relationship was found between any of the individual measures and destination accessibility (NDAI) of the built environment along the route and short walking trips. However, high walkability, based on both the BWI and EWI, was positively associated with short walking trips. In contrast, longer walking trips were not associated with either the individual or composite indices of built environment. Previous research by Mackenbach et al., (2016) did not measure associations between time spent walking and the environment along the route, therefore no comparisons can be made. Future research should aim to include the route environment when examining associations between the built environment and active transport, as it is potentially important for predicting walking behaviours.

The findings from these exploratory analyses indicate that associations between individual and composite indices of the built environment and time spent walking are sensitive to the type of neighbourhood delineation and spatial scale utilised. In addition, together with the home environment, other environments such as areas around destinations and along the route can be important in predicting time spent walking. Different ‘push’ and ‘pull’ factors of the built environment (Mackenbach et al., 2016) around the home, destination and route could potentially influence time spent walking. For example, areas around the home with high walkability and low slope could ‘push’ or encourage walking, and areas with high land use mix at the destination environment could ‘pull’ or attract walkers (Mackenbach et al., 2016). In addition, as shown in this research, the walkability of the environment along the route could facilitate short trips spent walking. Furthermore, previous research by Winters et al., (2010) also investigated the influence of the built environment around the origin, route and destination with cycling behaviour and found that characteristics of the route environment were more influential on healthy travel behaviours. Future research should investigate all three environments and associations with active transport behaviours and physical activity.

To achieve the ninth objective, the composite indices of walkability, (BWI and EWI) bikeability (BI) and neighbourhood destination accessibility (NDAI) were investigated in relation to active transport behaviours commuting to work, utilising data from the New Zealand Census (Chapter 6). In relation to the standard method (Frank et al., 2005) commonly employed in research with active transport behaviours, findings were consistent with previous research (Mayne et al., 2013), which found high walkability (based on three simple intensity based components, land use mix, street connectivity and dwelling density) was associated with increased likelihood of walking to work. In addition, the newly created kernel density measures of walkability, both the BWI and EWI, were positively associated with walking for transport. Furthermore, associations were stronger for the novel BWI indices (method 2 and 3) in comparison to the standard method (simple intensity, method 1), suggesting previous research could have underestimated the effect of the built environment in encouraging walking to work. Moreover, comparing the BWI and EWI methods, the EWI (comprising of novel land use mix, dwelling density, street connectivity, slope, street lights and footpaths and tracks measures) performed better than the BWI, lending credibility that the additional features included in the EWI capture or elucidate more of the context in which active transport takes place. While higher walkability, for both the BWI and EWI, was associated with walking to work, differences remained between the type of buffer (Euclidean or network) and neighbourhood scale utilised. Independent of demographic, socio-economic and neighbourhood deprivation factors, the EWI based on method 3, network buffer, at 800m was the best predictor of walking to work in comparison to all other methods and spatial scales.

Significant associations between neighbourhood destination accessibility and walking to work existed even after controlling for potential confounders. However, the effect sizes were small and therefore further analysis is recommended. Future research should consider the novel approach presented here when creating indices of walkability and for other types of walking such as walking for leisure or utilitarian purposes such as running errands, shopping etc.

The novel BI was significantly associated with cycling to work, however the effect sizes were small. This could be due to limitations in the underlying data on bike infrastructure in

Wellington City, which was restricted to density of bike racks and a small number of cycle lanes. Comparing between methods, Euclidean and network, and neighbourhood scale, the BI based on method 2 (Euclidean buffer), was best at predicting associations with cycling to work at both 1600m and 2400m. This finding requires further research as it was hypothesised that the BI based on the network buffer would predict stronger associations than the Euclidean buffer. In addition, there was no association between the BI at 800m, for either Euclidean or network buffer and cycling to work. This is unsurprising as it could be hypothesised that cycling as a transport mode usually takes place over distances greater than 800m.

Little to no association was found between neighbourhood destination accessibility (NDAI) and cycling to work, independent of demographic, socio-economic and area deprivation factors. Variables included as potential confounders had very little effect on the models. Similar to results for walking to work and destination accessibility, this finding is somewhat expected as destination accessibility is potentially unimportant to individuals cycling directly to work. Future research measuring the bikeability of the environment should include cycling for specific purposes such as leisure, work or utilitarian purposes (shopping, running errands, visiting health centres, etc.).

The findings from Chapter 6 confirm existing research findings in relation to the standard walkability index and walking to work (Mayne et al., 2013), and also add new findings in relation to the more nuanced methods of KDE with a vector component (buffers). In addition, high walkability, based on the EWI method 3, measured as an 800m network defined neighbourhood, had the strongest associations with walking to work.

In relation to the tenth objective, standard and novel indices of the built environment were tested with health outcomes, derived from the New Zealand Health Survey (NZHS) (Chapter 7). High walkability, for both the BWIs and EWIs based on methods 1, 3 and 4 were significantly associated with increased likelihood of meeting physical activity guidelines in the unadjusted models. However, no association was found after adjusting for neighbourhood deprivation, which attenuated the relationship between walkability of the built environment and physical activity. A possible explanation for this finding could be the use of a general measure of physical activity. Physical activity could include any form of activity such as walking, cycling, running, or sports activities, for transport, utilitarian or leisure purposes. Furthermore, previous research in New Zealand found positive associations between leisure-related physical activity and walking for all purposes but negative confounding by neighbourhood deprivation with transport related physical activity (Witten et al., 2012). It is possible that participants, from the NZHS used in this analysis mainly reported transport-related physical activity. However, the influence of neighbourhood deprivation cannot be determined as questions relating to the specific type of physical activity were not included in the NZHS. Further research into how neighbourhood deprivation can affect the relationship between walkability of the built environment and specific types of physical activity is necessary.

Regarding the second outcome variable tested, the likelihood of being overweight/obese (BMI ≥25) decreased as walkability of the built environment increased, however results varied by the type of method, neighbourhood delineation and scale used. Of note and independent of demographic, socio-economic and neighbourhood deprivation factors, high walkability, based on the standard BWI, (method 1, network buffer), was associated with 7% decreased likelihood of being overweight/obese at only one neighbourhood level, 2400m. In comparison, high walkability based on the novel EWI (method 3, network buffer) was associated with greater decreased likelihood of being overweight/obese at all three neighbourhood levels, 12% at 800m, 13% at 1600m and 12% at 2400m. In general, even after adjusting for neighbourhood deprivation, as walkability increased, the odds of being overweight/obese decreased for most methods and spatial scales. This finding is similar to some international research. For example, Pouliou and Elliott (2010) used a similar standard walkability index (based on housing unit density, an entropy index of land use mix and intersection density), and found a negative association with BMI in Vancouver, but not in Toronto, Canada (Grasser et al., 2013). In addition, Frank et al., (2009) reported a significant negative association between walkability (based on the standard method including housing unit density, entropy based land use mix, intersection density and retail floor area ratio) and BMI in men but not women (Grasser et al., 2013). However, results have been inconsistent in the international literature and further investigation into the relationship between walkability and overweight/obesity is required (Grasser et al., 2013). Importantly, the novel indices developed in this thesis, in particular the EWI based on method 3, the network buffer, proved to be the best predictor of associations between walkability and overweight/obesity across three neighbourhood levels, 800m, 1600m and 2400m. It is possible that previous research that has used the standard method of measuring walkability has underestimated the effects of the built environment on overweight/obesity health outcomes. Further research is required to investigate associations between different methods of measuring walkability and overweight/obesity health outcomes.

In relation to bikeability of the built environment and physical activity, high bikeability was associated with meeting physical activity guidelines, independent of demographic and socio-economic covariates. However, effect sizes were small ranging from 1%-2%. In addition, after controlling for neighbourhood deprivation, there was no relationship between bikeability and physical activity behaviours. It is possible that, similar to the walkability indices, neighbourhood deprivation has a mediating effect on the relationship between bikeability and physical activity. Further research into the mediating and moderating effects of neighbourhood deprivation on physical activity behaviours in bikeable environments is required.

High bikeability was significantly associated with reduced odds of being overweight or obese, at 1600m and 2400m in the unadjusted model. However after adjusting for demographic and socio-economic covariates, no association remained. In contrast, after additionally adjusting for neighbourhood deprivation, similar to the walkability indices, high bikeability was significantly associated with a decreased likelihood of being overweight or obese for both the Euclidean and network defined neighbourhoods and across all scales. In addition, similar to walkability, the BI based on method 3 (network buffer) at 2400m, had the lowest odds ratios, where the likelihood of being overweight or obese was 5% lower in high bikeable neighbourhoods. Creating areas that are conducive to cycling within 2400m of an individual's residence could potentially improve health outcomes such as prevalence of overweight and obesity. Previous research has not tested associations between bikeability and overweight/obesity, therefore no comparisons can be made. These findings need to be investigated further with future research creating indices specific to cycling and testing associations with health outcomes, as previous research has noted that elements of the built environment that influence walking are not necessarily the same for cycling (Wahlgren and Schantz, 2011, Winters, et al., 2011). Increasing physical activity through either walking or cycling can lead to increased energy expenditure and less likelihood of being overweight or obese. Altering the built environment to be more conducive to walking and cycling, by creating designated walk paths, separated bike lanes and bike parking, to name a few examples, could potentially yield important population health gains.

Associations between neighbourhood destination accessibility (NDAI) and physical activity were also investigated using the novel methods, 2 and 3, (Euclidean and network buffers), and for three neighbourhood scales, 800m, 1600m and 2400m. High destination accessibility was associated with meeting physical activity guidelines, independent of demographic, socio-economic and neighbourhood deprivation covariates. However, effect sizes were small, ranging from 1% to 2%, which could be due to the generality of the outcome measure used. Physical activity could encompass activity for a range of purposes such as leisure, transport or utilitarian. The physical activity outcome used in this research could potentially mask associations between leisure or utilitarian related physical activity and neighbourhood destination accessibility of the built environment. Further research is needed to test associations between the novel indices of neighbourhood destination accessibility and specific physical activity behaviours.

In relation to overweight/obesity, high neighbourhood destination accessibility was significantly associated with decreased likelihood of being overweight/obese for methods, 2 and 3 and across all spatial levels, after adjusting for demographic, socio-economic and neighbourhood deprivation covariates. This indicates that creating neighbourhoods that have accessible destinations within a 10-30 minute walk from residences could lead to important improvements in overweight/obesity health outcomes. It should be noted that, similar to physical activity outcome, the effect sizes were small, though previous research investigating the built environment and health outcomes has also reported small effect sizes (Witten et al., 2008). Further research is required to assess the associations between high neighbourhood destination accessibility and health outcomes.

8.2 Challenges and opportunities in measuring the built environment

For more than a decade, the use of GIS to objectively measure the built environment has gained considerable momentum. It is recognised as a useful tool to analyse spatially particular features such as measures of proximity, connectivity and density of the built environment with individual and household travel and physical activity behaviours (Saelens et al., 2003). In addition, objective measures can reduce measurement errors, allow for easy quantification and standardization and translation into transport and health policy changes (Lee and Moudon, 2004). In contrast, subjective measures such as environmental audits and surveys on the perceived environment around an individual’s home can be time consuming and costly due to in person observations of features of the built environment, as well as being subject to low response rates from participants (Brownson et al., 2009). GIS presents an opportunity to measure the built environment ‘remotely’, which can be less time consuming, and labour intensive, but time delays can arise in gaining access to data (Brownson et al., 2009). In addition, city councils and government departments are recognising the utility of analysing information spatially and are integrating GIS into their work processes. However, issues can arise for GIS technicians when trying to sort, clean and understand different data definitions from multiple jurisdictions without any common protocols (Brownson et al., 2009). The challenge remains for city councils and government departments to create a common standardisation of raw data and develop protocols to guide GIS technicians so that reliable comparisons between different jurisdictions can be made (Brownson et al., 2009).

Challenges remain in the many ways ‘neighbourhood’ is conceptually defined in the literature. Studies commonly use either territorial or administrative neighbourhood definitions, based on collective historical, social or population characteristics, or ego-centric definitions of neighbourhoods based on environments around the individuals’ residences (Chaix et al., 2009). These two approaches represent ‘fixed’ (administrative) versus ‘sliding’ (buffers for exact individual residences) neighbourhood boundaries (Chaix et al., 2009). However, due to limitations of arbitrarily defined administrative neighbourhoods, which do not necessarily represent individual exposures, ego-centric neighbourhoods are used as a way to capture the local exposure area (Chaix et al., 2009). In addition, ego-centric buffers can also exclude space beyond the boundary, which could influence physical activity behaviours. Generating ‘fuzzy’ neighbourhood delineations present a smoother transition between inner and outer neighbourhood boundaries (Chaix et al., 2009). Creating kernel densities of built environment features around an individual’s residence can provide a continuous surface of neighbourhood exposure, representing a ‘fuzzy’ neighbourhood delineation. This thesis research used a combination of both approaches in two different ways; first, KDE measures of the built environment were created and then averaged to Euclidean and network buffers, (vector component), around individual residences and destinations from the New Zealand Household Travel Survey; second, KDE measures were averaged to the network and Euclidean buffers, (vector component), around meshblock population weighted centroids (PWC) in order to test associations with secondary data collected at the meshblock level (Census and New Zealand Health Survey). The second approach was necessary as access to individual addresses was not possible, whereas in an ideal scenario geographic locations would be provided in order to create individual local environmental exposures.

In addition, the issue of scale is interlinked with the concept of ‘neighbourhood’. Creating multiple buffers based on a straight line (Euclidean) or along the road network (network) from the individual’s residence or PWC at various scales has been used as a way to ‘capture’ built environment exposures theorised to influence active transport and physical activity behaviours (Chaix et al., 2009). This thesis research identified the network buffer, based on statistical models, as the best neighbourhood walkability buffer (EWI) to predict walking to work and its relationship with overweight/obesity. However, the challenge remains when trying to determine the most appropriate neighbourhood scale to measure associations between the built environment and active transport and physical activity. Emerging technologies, such as global positioning systems (GPS), accelerometers, smart phone applications and life-logging (Hurvitz et al., 2014) present opportunities for increased measurement precision of physical activity behaviours, enabling more targeted interventions in built environment settings (Graham and Hipp, 2014). For example, recent work by Hwang et al., (2016) quantified walking bouts as they occurred in space and time using accelerometers and GPS to objectively measure walking behaviours. They found that these methods allowed increased precision of the locations where actual walking takes place and confirmed previous findings where walkability of the built environment was positively associated with high walking counts. Further, developing activity-space exposure models (Chaix et al., 2009) that capture actual and potential activity spaces based on individual travel behaviours (Madsen et al., 2014) could help identify features of the built environment that encourage or hinder physical activity behaviours.

Measuring multiple features of the built environment, combining them into indices, and creating maps, can present an opportunity to communicate results to policy makers and address issues of multicollinearity in statistical models (Saelens and Handy, 2008; Brownson et al., 2009). Additionally, creating indices for specific transport modes, not just walking can be useful in identifying features of the built environment that facilitate or hinder physical activity behaviours. The ways in which walkers and cyclists navigate the built environment can be different depending on topography and street connectivity (Berrigan et al., 2015). It is also possible that access to public transport can influence physical activity behaviours. For example, previous research by Mavoa et al., (2012) objectively measured public transit accessibility in conjunction with walking accessibility and a measure of transit frequency. They argued these objective measures could be used to identify areas where people could substitute to non-car modes such as walking and public transit use, and also identify areas where public transit frequency and access could be improved. Similar to Mavoa et al., (2012), creating specific indices for walking, cycling and destination accessibility in this thesis can help in identifying areas in need of modifications to encourage physical activity behaviours and destinations that attract walkers and cyclists in their neighbourhood environment. However challenges remain in conceptually matching characteristics of the built environment with specific physical activity behaviours (Ding and Gebel, 2012; Saelens and Handy, 2008). Mode specific indices should be based on conceptually acceptable links with attributes of the built environment. For example, this research included bike infrastructure components in the BI that were conceptually matched with influencing cycling behaviours.

Much of the research on the built environment and active transport and physical activity has measured the neighbourhood environment around the residence (Kerr et al., 2013; Manaugh and El-Geneidy, 2011; Saelens and Handy, 2008). It is assumed that physical activity is restricted to the residential neighbourhood, however, this is not necessarily true. For example, in the case of active transport, the built environment along the route or at the destination could also be important in encouraging active transport behaviours. As part of this thesis, the built environment in three environments, the home, destination and route, were investigated in relation to time spent walking (Chapter 5). Even though the sample size was small, the analysis revealed a variation in associations with time spent walking, depending on the type of built environment feature, neighbourhood delineation and spatial scale used for the home, destination and route environments. Future research should investigate areas beyond the residential neighbourhood as destination and route environments could also be important areas for encouraging active transport and physical activity behaviours (Winters et al., 2010; Mackenbach et al., 2016; Vale and Pereira, 2016).

8.3 Methodological contributions

This study has made a number of important original methodological contributions and innovations to quantifying the built environment and validating associations with active transport, physical activity and health outcomes. The main original contributions were:

First, the development and comprehensive testing of a novel Basic Walk Index (BWI) associated with active transport, physical activity and overweight/obesity in adults. The novel BWI was compared and contrasted with the standard BWI that is regularly replicated in the literature. Results demonstrated that the novel BWI method had stronger associations with active lifestyle behaviours and health outcomes than the standard BWI method. After further refinement and improvement of the novel BWI

Second, further refinement of the novel BWI by creating an Enhanced Walk Index (EWI) that included additional elements of the built environment associated with walking (slope, street lights and footpaths and tracks). The EWI was comprehensively tested for associations with active transport, physical activity and overweight/obesity and was found to be improvement on the novel BWI with stronger associations with active lifestyle behaviours and health outcomes. In addition, the combination of both the novel method and the additional features included to create the novel EWI resulted in the strongest associations. Replication of this novel method and EWI in other locations is necessary to ensure validity and comparability of the method and index. Both the standard and novel methods were tested and validated against two self-reported secondary datasets, the Census and NZHS. This is the first study in New Zealand to create novel walk indices (BWI and EWI) and compare them with an existing standard walk index (BWI).

Third, the development and comprehensive testing of a novel bikeability index with cycling behaviours and health outcomes. The index was based on conceptually matched features of the built environment with cycling behaviours, including land use mix, street connectivity, slope, street lights, bike racks and cycle lanes. This is the first study to develop an index of bikeability for a city in New Zealand based on the novel method and test associations with active transport, physical activity and overweight/obesity health outcomes.

Fourth, the development and comprehensive testing of a novel neighbourhood destination accessibility index (NDAI). This index represents an alternative to the original NDAI created by Witten et al., (2011) which was based on the standard method (simple intensity). This is the first study to create a NDAI based on the novel method presented in this thesis and test associations with active transport, physical activity behaviours and health outcomes in a New Zealand context.

Fifth, measurement and testing of associations between time spent walking and novel individual built environment measures (land use mix, street connectivity, dwelling density, slope, street lights and footpaths and tracks) and novel walk indices (BWI and EWI) in three different environments. The built environment around the home, route and destinations were investigated for associations with time spent walking. While this was a pilot study (Chapter 5), with a small sample size, the findings are interesting and potentially reflect the importance of examining other environments outside of the residential neighbourhood.

Sixth, each of the novel indices (BWI, EWI, BI, NDAI) were created and comprehensively tested for two neighbourhood delineations (Euclidean and network) and at multiple spatial scales. In general, neighbourhood delineations based on the network buffer had stronger associations with active transport, physical activity and overweight/obesity health outcomes. This is the first study in New Zealand to examine the influence of both types of neighbourhood delineations, at a range of scales with a number of active and health-related outcomes.

Taken together, these methodological contributions advance current understandings in the field of the built environment and health research and represent an original contribution to knowledge.

8.4 Limitations and strengths

The built environment measures developed and examined in this research were tested with cross-sectional data, which limits identification of any causal relationships. Additionally, due to the cross-sectional design, it was not possible to account for self-selection and how it impacted on residential choices and active transport and physical activity behaviours. Further, each of the active transport and physical activity measures were self-reported and could be subject to social desirability bias and under or over reporting. Nevertheless, previous cross-sectional research has found consistent links with the built environment and physical activity behaviours in adults (Oliver et al., 2015; Sallis et al., 2012) using available secondary datasets. In addition, advantages of using self-reported data can be ease of access, low associated costs in comparison to using GPS technologies and relatively fast data analysis with objective measures. Furthermore, this research did not investigate independent associations of the built environment for specific sub groups such as children, older adults, ethnic minorities, males/females and the disabled.

A potential limitation to the novel method was the use of a fixed bandwidth in the kernel density estimation. The fixed bandwidth of 500m was chosen after initial testing with bandwidths ranging from 300m to 800m, the 500m had the strongest associations. Possible methodological improvements could be calculating the kernel density using an adaptive bandwidth based on the underlying residential density (Buck et al., 2015a; Carlos et al., 2010).

Further limitations include: the objective GIS measures were created for Wellington City only and were unable to be verified with on-site visits of the physical environment due to time and budget constraints. Data for the NDAI ranged from 2008-2015, which does not fully correspond to the years in which active transport or physical activity behaviours were measured (HTS 2010/11-2013/14, Census 2013 and NZHS 2011/12-2015/16). There is also a possibility that the built environment could have changed in the years between surveys. However, these are likely to be minor as major changes to the built environment usually take a number of years to complete.

In addition, using GIS to measure the geographical access to destinations does not necessarily equate with access on the ground and other subjective perceptions of safety, quality and desirability of destinations could also impact on physical activity behaviours (Witten et al., 2011)..

Due to small sample sizes in the HTS and NZHS, multiple years were combined to increase statistical power; therefore, results need to be interpreted with caution. Moreover, the

HTS and NZHS surveys were unweighted and as such cannot be generalised to the whole of New Zealand. However, developing measures specific to local contexts offers evidence for local transport and health policy makers to modify and improve the built environment in their own urban areas.

Despite these limitations, there were a number of key strengths underpinning this research. Multiple features of the built environment were created using an alternative and novel method. These features were examined separately and together in the form of composite walk indices with active transport behaviours using data from the HTS. In addition, various walk, bike and neighbourhood destination accessibility indices were developed using the novel method to quantify the built environment for active transport, physical activity and overweight/obesity health outcomes, using data from the Census and NZHS. Another strength is the thorough examination of each of the individual and composite indices after adjusting for potential demographic, socio-economic and area deprivation confounders at multiple spatial levels and different neighbourhood delineations. A further strength of this study was the comparison of the standard walk index with an alternative walk index, along with stronger associations being found with the latter. This finding potentially indicates that previous research has underestimated the influence of the built environment on active transport, physical activity and overweight/obesity health outcomes. In addition, the neighbourhood built environment was operationalised in a number of ways using different delineations and multiple scales to test associations. Lastly, visualising the many ways different methods and built environment phenomena are represented spatially, depending on the type of method, delineation and spatial scale utilised, drew attention to the importance of method choice in research on the built environment.

8.5 Research implications

Identifying and utilising appropriate data and methods to measure the built environment for active transport and physical activity form part of the foundation upon which results and findings are built. There is a clear need to continually investigate standard methods and advance them by addressing inherent limitations. Proposing alternative, more specific, approaches of measuring the built environment for active transport and physical activity behaviours can result in a more accurate evidence base from which to draw and ensures continued progression of research on the built environment. Developing more precise methods strengthens the support for creating neighbourhoods that are conducive to active transport and physical activity. For example, utilising appropriate methods to identify areas that have low walkability and bikeability can help town planners, local and central government agencies, property developers and urban designers, identify areas that need to be modified to enhance walking and cycling for leisure, utilitarian and transport purposes.

Creating environments to enable rather than hinder physical activity can lead to improved individual and wider population health, reducing current and future burdens on the health system. Specifically, focusing resources on preventative approaches such as improving the built environment to facilitate physical activity behaviours, rather than curative approaches such as treating diseases associated with physical inactivity and obesity, can have significant positive effects for the economy, health system and society as a whole. The findings from the alternative method proposed in this research could be used by health policy advisors, transport planners and urban designers to advocate for improved policies and distribution of government resources to be allocated for improving the neighbourhood built environment. Cross collaboration between multiple groups from health, transport and urban design fields is necessary in order to reduce health system costs, improve public health and quality of life, reduce carbon emissions and create or modify existing neighbourhoods to encourage physical activity for all types of purposes and kinds of people. Some of the interventions and modifications necessary to improve the health and liveability of neighbourhoods span the health, transport and urban design fields, for example, zoning land for high residential density and mix of businesses, ensuring destinations such as shops, work and parks are accessible within a certain distance of residences, restricting car speeds in residential areas, improving footpath quality and connectivity and providing street lights, parks and recreation areas to encourage physical activity behaviours. A better distribution and utilisation of public taxes and government resources can be achieved by taking a preventative and collaborative approach.

Developing, validating and adopting improved methods, such as the novel approach presented in this thesis, to measure the built environment for active transport and physical activity represents an intrinsic part of the evidence base in order identify where further improvements can be made.

8.6 Future research

In order to identify how active travel, physical activity behaviours and health outcomes are influenced by the physical environment, further research replicating and validating the alternative novel method, developed in this thesis, for different population groups and built environment contexts is necessary. For example, replicating the novel method for other cities in New Zealand and internationally would help contribute to the value of the novel method for research on the built environment and health. Measuring the built environment for specific sub groups such as children, older adults, ethnic minorities and the disabled is necessary in order to identify specific features or combinations of characteristics of the built environment that facilitate or hinder physical activity. This research is necessary for improving related health outcomes for all members of society. In addition, future research should utilise longitudinal data rather than cross-sectional data to help overcome issues related to self-selection, enabling identification of the causal association between elements of the built environment and physical activity behaviours (Ding and Gebel, 2012).

Future research should investigate and validate objective KDE measures of the built environment with subjective perceptions of urban safety, quality and attractiveness of destinations, which can also impact physical activity behaviours (Witten et al., 2011). In addition, utilising emerging technologies such as GPS, mobile applications and life-logging offers more precise objective measures of where, when, and how active transport and physical activity behaviours take place in the built environment. Future research should measure the built environment for specific physical activity behaviours and purposes, such as walking or cycling for transport, leisure or utilitarian reasons, and identify the most appropriate scale and type of neighbourhood delineation depending on the outcome measured.

Furthermore, in relation to individual data available from the HTS, this research used data relating to time spend walking directly from home to any destination. Future research could test the novel method with multiple trips of walking, cycling and public transport use for multiple purposes in home and destination settings.

8.7 Thesis conclusion

This is the first study to measure the relationship between novel measures of the built environment and active transport, physical activity and overweigh/obesity in adults in New Zealand. It is also the first study to compare existing standard methods of quantifying walkability with an alternative, more nuanced and novel method. In addition it is the first to create indices of bikeability and neighbourhood destination accessibility based on the novel method. Positive associations were observed for the standard and novel methods of walkability, bikeability, NDAI and active transport and overweight/obesity health outcomes. Further, the novel method of walkability (BWI) based on the network defined neighbourhood was found to have stronger associations with active transport behaviours and overweight/obesity than the standard method frequently employed in research on the built environment, suggesting the novel method is valid. Moreover, the novel EWI had stronger associations than the novel BWI, potentially suggesting that including other relevant attributes of the built environment theorised to influence active transport behaviours is important. This research suggests that it is critical to continually strive to improve and address the limitations of the standard methods used in research on the built environment, active transport and physical activity in order to have better confidence in the evidence of associations. This research strengthens current international and national evidence that the built environment affects active transport and physical activity behaviours. Creating environments conducive to walking and cycling for all purposes could lead to significant population health benefits, while improving the quality of life in urban communities.

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Appendix A

Table 49. Summary statistics of individual exposure measures for the home and destination Euclidean and network buffers.

Exposure measures	**Home Address *Euclidean buffer***	**Home Address *network buffer***	**Destination Address *Euclidean buffer***	**Destination Address *network buffer***
Land use mix		**Mean (Std)**		
400m	6.84(1.90)	6.85(1.97)	7.18(1.58)	7.07(1.72)
800m	6.92(1.37)	6.86(1.77)	7.32(1.11)	7.08(1.44)
1200m	7.20(0.84)	6.88(1.35)	7.52(0.78)	7.13(1.22)
1600m	7.42(0.51)	6.94(0.99)	7.57(0.58)	7.27(0.99)
2000m	7.56(0.44)	7.07(0.83)	7.50(0.53)	7.39(0.77)
2400m	7.60(0.43)	7.21(0.71)	7.41(0.52)	7.44(0.64)
Street connectivity				
400m	8.78(1.66)	8.89(1.61)	8.79(1.76)	9.03(1.07)
800m	8.60(1.35)	8.93(1.38)	8.52(1.54)	8.99(1.43)
1200m	8.34(1.06)	8.87(1.16)	8.23(1.32)	8.89(1.81)
1600m	8.07(0.87)	8.79(0.97)	7.90(1.19)	8.78(1.02)
2000m	7.72(0.86)	8.67(0.82)	7.60(1.11)	8.65(0.88)
2400m	7.42(0.91)	8.56(0.66)	7.33(1.08)	8.57(0.75)
Dwelling density				
400m	8.11(1.59)	8.26(1.57)	7.82(2.02)	8.11(1.97)
800m	7.66(1.19)	8.29(1.37)	7.57(1.64)	8.09(1.65)
1200m	7.44(0.99)	8.09(1.17)	7.30(1.36)	8.04(1.37)
1600m	7.24(0.96)	7.98(1.01)	6.99(1.19)	7.95(1.15)
2000m	6.92(1.01)	7.90(0.94)	6.82(1.09)	7.80(0.99)
2400m	6.63(1.08)	7.84(0.87)	6.66(1.06)	7.71(0.89)
Slope				
400m	3.40(2.52)	3.36(2.88)	4.04(1.99)	3.98(2.30)
800m	3.20(1.28)	3.20(1.92)	3.73(1.40)	3.80(1.90)
1200m	3.36(0.88)	3.19(1.53)	3.56(0.96)	3.55(1.53)
1600m	3.50(0.86)	3.22(1.36)	3.64(0.78)	3.40(1.32)
2000m	3.73(0.78)	3.22(1.19)	3.76(0.69)	3.30(1.16)
2400m	3.88(0.60)	3.24(1.11)	3.80(0.61)	3.30(1.05)
Street lights				
400m	8.06(1.41)	8.19(1.42)	8.03(1.87)	8.35(1.67)
800m	7.81(1.34)	8.18(1.38)	7.65(1.68)	8.29(1.48)
1200m	7.52(1.18)	8.13(1.23)	7.34(1.54)	8.13(1.34)
1600m	7.20(1.16)	8.04(1.09)	7.03(1.44)	7.99(1.24)
2000m	6.83(1.23)	7.90(1.04)	6.81(1.39)	7.86(1.16)
2400m	6.57(1.32)	7.78(1.01)	6.64(1.35)	7.78(1.10)
Footpaths and tracks				
400m	9.54(0.67)	9.66(0.61)	9.33(1.07)	9.52(0.90)
800m	9.27(0.71)	9.63(0.53)	9.16(0.98)	9.50(0.74)
1200m	9.09(0.70)	9.54(0.42)	8.97(0.89)	9.45(0.59)
1600m	8.92(0.68)	9.44(0.39)	8.72(0.84)	9.40(0.49)
2000m	8.62(0.67)	9.35(0.40)	8.47(0.87)	9.31(0.45)
2400m	8.36(0.78)	9.28(0.37)	8.27(0.94)	9.24(0.42)

Table 50. Summary statistics of composite exposure measures for the home and destination Euclidean and network buffers.

Exposure measures	Home Address *Euclidean buffer*	Home Address *network buffer*	Destination Address *Euclidean buffer*	Destination Address *network buffer*
Basic Walk Index[a]		**Mean (Std)**		
400m	23.69(3.54)	23.98(3.58)	23.79(3.87)	24.22(3.93)
800m	23.06(2.86)	24.01(3.28)	23.27(3.74)	24.08(3.52)
1200m	22.75(2.65)	23.77(2.69)	22.73(3.63)	23.97(3.02)
1600m	22.33(2.70)	23.65(2.36)	21.84(3.49)	23.90(2.60)
2000m	21.49(2.77)	23.57(2.29)	20.94(3.49)	23.75(2.28)
2400m	20.67(2.93)	23.53(2.13)	20.19(3.54)	23.60(2.04)
Enhanced Walk Index[b]				
400m	43.97(6.01)	44.31(5.80)	44.72(7.15)	45.64(7.04)
800m	42.92(4.89)	44.59(5.44)	43.38(6.68)	45.25(6.01)
1200m	42.33(4.61)	44.26(4.67)	42.18(6.14)	44.78(5.19)
1600m	41.56(7.75)	44.05(4.25)	40.76(5.84)	44.40(4.57)
2000m	40.22(4.83)	43.79(4.09)	39.35(5.87)	43.98(4.10)
2400m	38.89(5.13)	43.62(3.76)	38.10(6.05)	43.68(3.70)
Neighbourhood Destination Accessibility Index[c]				
400m	8.78(0.98)	8.78(1.09)	9.21(1.25)	9.29(1.23)
800m	8.81(0.85)	8.91(0.89)	8.80(1.16)	9.21(1.10)
1200m	8.70(0.85)	8.97(0.74)	8.49(1.13)	9.05(0.91)
1600m	8.34(0.94)	8.98(0.72)	8.19(1.17)	8.94(0.80)
2000m	7.99(1.14)	8.87(0.76)	7.87(1.29)	8.84(0.78)
2400m	7.74(1.27)	8.71(0.75)	7.62(1.41)	8.74(0.76)

[a] The Basic Walk Index is comprised of the sum of three components, standardised to deciles, land use mix, street connectivity and dwelling density. The raw values range from 3-30, values close to 30 indicate high basic walkability.
[b] The Enhanced Walk Index is comprised of the sum of six components, standardised to deciles, land use mix, street connectivity and dwelling density, slope, street lights and footpaths and tracks. The raw values range from 6-60, values close to 60 indicate high enhance walkability.
[c] The Neighbourhood Destination Accessibility Index is comprised of the sum of eight deciled components, education, transport, recreation, social and cultural, food retail, financial, and health and other retail. The raw values range from 8-80, values close to 80 indicate high destination accessibility.

Table 51. Summary statistics of individual and composite exposure measures for the route between home and any destination.

Exposure measures	**Route *buffer***	
	50m	***100m***
	Mean (Std)	
Land use mix	6.91(1.62)	6.90(1.60)
Street connectivity	9.13(1.57)	9.10(1.57)
Dwelling density	8.41(1.68)	8.35(1.67)
Slope	3.99(2.50)	3.94(2.40)
Street lights	8.51(1.53)	8.49(1.52)
Footpaths and tracks	9.68(0.72)	9.65(0.73)
BWI	24.43(3.57)	24.34(3.54)
EWI	46.31(6.92)	46.08(6.77)
NDAI	9.15(1.15)	9.14(1.12)