An exploration of the effects of the Built Environment on Depression in the Wellington Region, New Zealand

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By

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Abstract

Background: Depression is a major epidemic affecting millions of people globally. One of the most widely recognised contributors to this global epidemic is the decline in active transport and physical activity. To address this issue research has focused considerably on quantifying the walkability of neighbourhood areas in an attempt to measure the influence of the built environment on active transport and physical activity. A large proportion of this research has exclusively focused on adults, leaving a significant gap in knowledge in terms of the influence of the built environment on young people's mental health. Young people are highly susceptible to the effects of their built environments as they can have restricted mobility due to those under 16 years being unable to drive.

The aim of this research was to investigate the relationship between the built environment and depression amongst adolescents aged 12 to 18 years in the Wellington Region, New Zealand (NZ).

Methods: A measure of the built environment was obtained by developing a walkability index, based on previously developed indices and measures. The measures used in this research were dwelling density, intersection density, mean normalized difference vegetation index (NDVI), average traffic volume and land-use mix. Both Euclidean and network buffer methods were employed as measures of the neighbourhood area, using a weighted population centroid with a distance of 800m. Depression was measured using the Reynold Adolescent Scale, sourced from the Youth'12 National Youth Health Survey by The University of Auckland Adolescent Health Research Group. Zero-inflated negative binomial regression was used to investigate any possible associations. Sex, age, prioritised ethnicity and household deprivation were included in the analysis as confounders.

Results: The results obtained from the index validation process indicate that the built environment is associated with an increased likelihood of active travel to work for the 800m Euclidean buffer after accounting for sex, age, ethnicity, and socioeconomic factors. While the network-based buffer showed no significant association for both the count and zero-inflated models. Findings from the regression analysis between walkability (Euclidean buffer) and adolescent depression suggest that as walkability increases depressive symptoms in adolescent decrease. These suggest that living in a walkable neighbourhood results in lower depressive symptoms.

Conclusions: The results add to the body of evidence that improving walkability has a positive impact on young people's mental health.

Acknowledgements

If you educate a man, you educate one individual, but if you educate a woman, you educate a family.
~Fante Proverb

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Abbreviations

WHO	World Health Organization
MoH	Ministry of Health
DSM-5	Diagnostic and Statistical Manual of Mental Disorders
ZINB	Zero-inflated negative binomial
AIC	Akaike's information criterion
BIC	Schwartz's Bayesian information criterion
NB	Negative binomial
RADS	Reynolds Adolescent Depression Scale
AADT	The average daily traffic volume at a given location over a year
NDVI	Normalized difference vegetation index
MELAA	Middle Eastern, Latin American and African
SMD	Standardized mean difference
NZHS	New Zealand Health Survey
PRIMHD	Programme for the Integration of Mental Health Data
PWC	Population weighted centroid
LUM	Land-use mix
GLM	Generalised linear model
M	Meters
M^2	Meters Squared
NZ	New Zealand
SMD	Standardised mead difference
RCA	Regional council authorities

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Chapter 1: Introduction

Burden of disease

Depression is one of the most important causes of mental illness and disability. Globally, over 300 million people are living with depression (World Health Organization (2017). According to the New Zealand Mental Health Foundation, 6% of adults have experienced psychological distress (C. H. Lee, Duck, & Sibley, 2017). Research has shown that individuals experiencing psychological distress are likely to have an anxiety or depressive disorder (C. H. Lee et al., 2017). In adolescents, results from the Youth'12 National Youth Health Survey showed that 16% of female students and 9% of male students reported depression symptoms that were likely to be clinically significant. Depression causes severe symptoms that affect how we function, feel and think (Egede & Ellis, 2010). In young people, depression presents itself differently to adults; adolescents convey sadness through moodiness, distrust, aggression, or having angry outbursts (Reeves, Postolache, & Snitker, 2008).

Built environment and health

An individual's home and work environment can influence their mood, behaviour, and social interacts with others. Importantly, it can create and reduce stress, which influences not only their emotional but also their physical health and well-being. As the global population increases, it is becoming critical that we gain an understanding of how the complex built environment affects health. The built environment has been shown to have both direct and indirect influences on health. Environmental characteristics of the built environment such as household crowding, air quality and noise pollution have direct effects on health. Indirectly, the built environment may influence health by changing psychosocial processes amongst those with known health conditions. Overall, gaining an understanding of how health outcomes are influenced by the built environment, and where the individuals at greatest risk are likely to be to be found, will help to target assistance to those areas and develop healthier environments in the future.

Built environmental and depression

The effect of the neighbourhood environment as a potential determinant of mental disorders has been explored over many years. Research conducted by Faris and Dunham (1939), showed that socially disorganized neighbourhoods along with compositional factors (i.e age, sex, ethnicity, employment, and income) and pathologies (such as substance abuse, crime, and stigmatization) resulted in a feeling of isolation, which was shown to trigger mental health problems. A consequence of the Faris and Dunham (1939) study was the development of interest in the relationship between mental health and social class, which led to the development of the social stress model. The model theorises that stressful and lasting life events and complications cause psychological stress, contributing to mental health problems, especially if an individual lacks social support (Turner, Wheaton, & Lloyd, 1995). Therefore, the physical and social neighbourhood environment can act as either a safeguard or stressor of anxiety and stress, affecting depression.

1.2 Rationale

Previous studies that have examined the influence of the built environment on depression have largely focused on adults (Miles, Coutts, & Mohamadi, 2012; Saarloos, Alfonso, Giles-Corti, Middleton, & Almeida, 2011; Sallis et al., 2009; Wilbur et al., 2009). In this thesis the focus is on youth, because youth are more vulnerable to the influences of the built environment. Secondly, they tend to have restricted mobility due to a large proportion of them being unable to drive (those under 16 years). Moreover, adolescence is a period when depression often first emerges (Thapar, Collishaw, Pine, & Thapar, 2012). Therefore, an investigation into the risk factors of depression among the adolescent population can provide new knowledge to support the development of intervention strategies at the neighbourhood-level and help to focus depression screening in less-walkable areas. Presently, no literature has investigated the relationship between depression and neighbourhood walkability in the New Zealand context. This thesis addresses this gap in the literature.

1.3 Research aim and questions

The thesis aims to develop and validate a walkability index and to use it to investigate the possible association between the built environment and poor mental health. This will be conducted by exploring the effect of low walkability on depression symptoms among adolescents living within the urban areas of the Wellington Region. The walkability index will be developed using the following measures: intersection density, land-use mix, dwelling density, average traffic volume and mean NDVI.

The investigation into the association between mental health and the built environment is guided by the following research questions:

Question 1: Does the walkability index developed in this study explain observed active travel to work?

Question 2: Is there an association between walkability and depression, as measured by the Reynolds Adolescent Depression Scale (RADS)?

1.4 Thesis structure

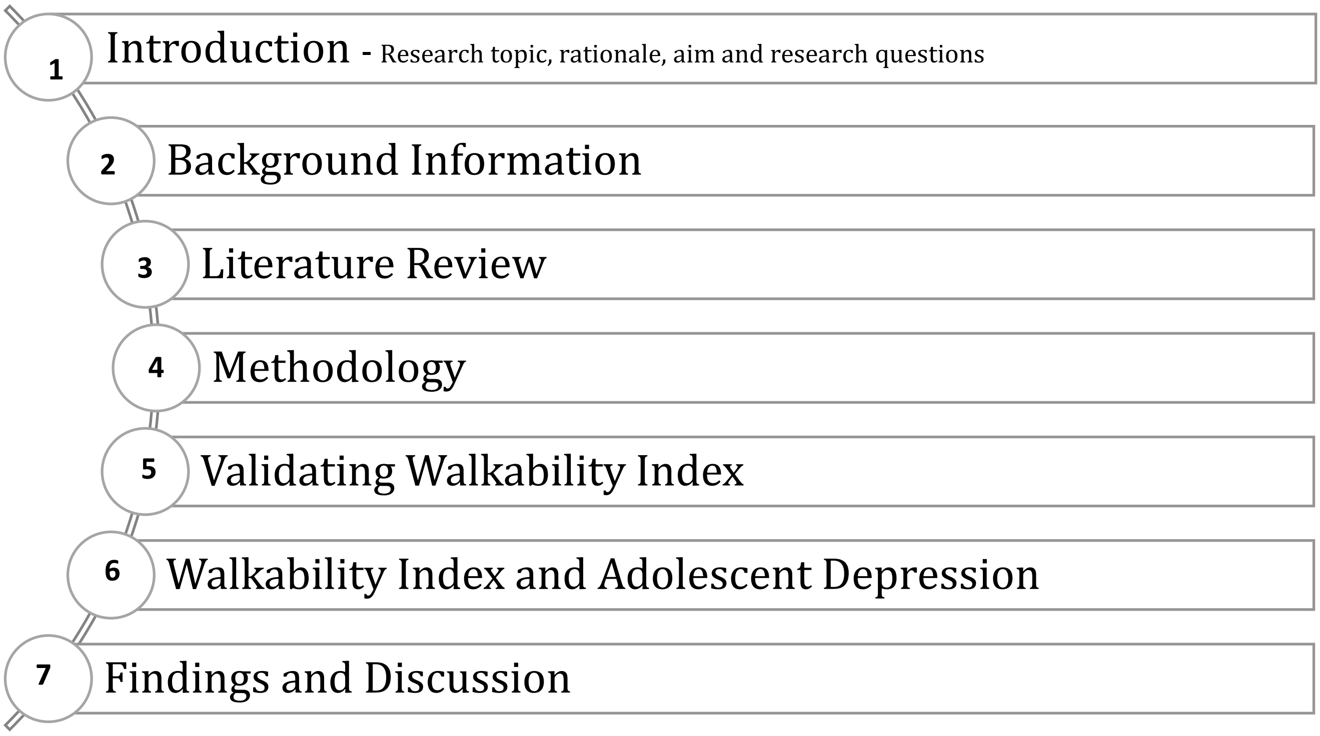


Figure 1. Schema of the focus of each chapter

Chapter 1 introduces the research topic and presents the rationale, aim and research questions.

Chapter 2 offers background information and definitions on the topics central to the thesis; walkability, walkability indices, adolescents, depression and the built environment.

Chapter 3 reviews the literature and includes sections on the socioecological framework, the importance of place and factors that determine health (such as the built environment and genetics). It critically reviews the relevant New Zealand and international literature, highlighting important findings and identifying gaps in knowledge**.**

Chapters 4, 5 and 6 detail the development of built environment measures and the construction of the walkability index.

Chapter 4 presents the methodology and data sources used to develop the walkability index, outlines the health data and justifies the use of meshblocks and buffers as a measure of neighbourhood area.

Chapter 5 tests the validity of the walkability index developed in chapter three using data on "main means of travel to work" from the 2013 NZ Census.

Chapter 6 presents the results of the regression analysis between the walkability index and health data on adolescent depression.

Chapter 7 presents the discussion of the main findings and an overview of the challenges and opportunities of measuring walkability. The final section of the chapter concludes by discussing how this research will contribute to future research on walkability.

Chapter 2: Background information

2.1 Walking and cycling

According to Forsyth and Southworth (2008), walking and cycling are two of the most important underpinnings of a sustainable city. These modes of travel not only provide environmental benefits as an alternative to motor vehicle use, but choosing to walk or bike instead of using a motor vehicle helps to reduce air and noise pollution and oil dependency. Consequently, there is a lowering of greenhouse gases emitted into the atmosphere aiding in the mitigation of climate change (Chapman, 2007). Economically, walking provides benefits to local businesses by increasing foot traffic, therefore increasing the number of potential customers. A study conducted in Melbourne, Australia by Acland Street Precinct Traders (2003), showed that more than half of the spending in the Acland Street Precinct was from walkers, while only a small percentage was from motor vehicle users (26%). Overall, the study found that walkers spent more yearly than those in motor vehicles (Acland Street Precinct Traders, 2003).

Socially, walking increases the potential for social interactions, creating a socially supportive environment. A higher number of people on the streets contributes to a sense of safety due to the increased number of “eyes on the street” (Brown et al., 2008). Walking and cycling are the most accessible forms of exercise for reducing the risk of negative health outcomes such as obesity and cardiovascular disease. These findings are supported by the World Health Organisation (WHO), which has shown that exercising a total of 30 minutes a day on most days of the week, even if carried out in short episodes, is useful in providing significant health benefits (Dora, Phillips, & Phillips, 2000).

Walking and cycling can play a critical role in helping individuals feel better, by helping to reduce stress and improve mood. A meta-analysis exploring the association between regular physical activity and depression found that walking and cycling have a significant antidepressant effect on individuals with depression (Standardized mean difference (SMD) adjusted for publication bias =1.11 (CI 0.79-143)[1](Mutrie, 2003). In terms of adolescents, a recent study exploring the treatment effect of physical activity on depressive symptoms in adolescents found that exercise has modest benefits for teens who are already undergoing treatment for depression(Carter, Morres, Meade, & Callaghan, 2016). Overall, walking and cycling are the most equitable forms of transport, regardless of socioeconomic status and education as most people can participate in it. Both modes of travel have many benefits for the community and individuals. However, to realise these benefits, the built environment must be able to

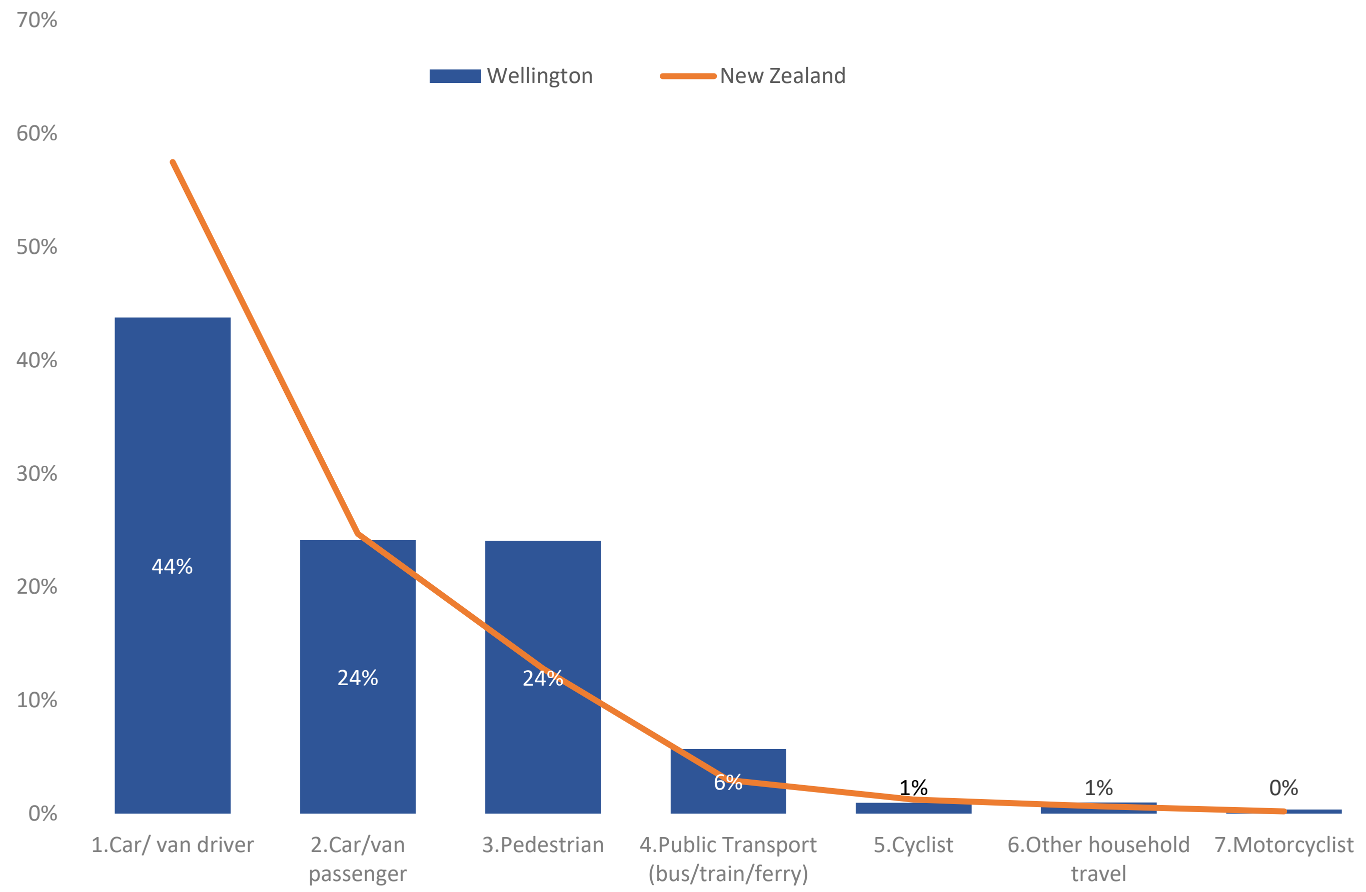
[1] 95%CI = 95% confidence interval

provide a safe, accessible and convenient environment to allow people to make changes to their current modes of travel.

The current situation in the Wellington Region and New Zealand

Before exploring how the built environment can encourage walking and cycling and therefore improve mental health in adolescents, the current state of active travel in New Zealand and the study area (Wellington Region) is discussed below.

Figure 2 shows that motor vehicles are the preferred mode of transport nationally and in the Wellington region (approx. 68% in Wellington and 82% in New Zealand).



Source: Ministry of Transport (2017)

Figure 2. Mode share of trip legs 2015 – 2017

Walking and cycling make up 25% of the region's daily trips, compared to 14% nationally. Overall, the Wellington Region has lower levels of motor vehicle use and higher levels of active travel in comparison to the national average. This overview indicates that although regional data is indicating high levels of walking and cycling, more work is required at the national levels to make walking and cycling safe and accessible. It shows that in order to improve the mental health of all individuals, national-level initiatives need to be implemented. Therefore, this study should be regarded as a proof of concept to test the feasibility of developing a national-level walkability index that can be used to inform nation-level initiatives.

2.2 The built environment

According to urban planners, the "built environment" refers to urban design, land-use, transportation systems and the patterns of human activity that occur within each of these elements. "Urban design" refers to the look, form and function of the city and the physical features within it. "Land use" usually refers to the allocation of activities across space. The "transportation system" refers to physical infrastructure such as roads, footpaths, cycle lanes, railroad tracks, bridges. (Handy, Boarnet, Ewing, & Killingsworth, 2002). These three characteristics must compliment and balance each other in order to influence active travel and physical activity.

In order to increase the number of people walking and cycling, elements of the built environment such as population density, mixed land use, and street network design must be examined as they are among the strongest predictors of active travel. Walking and cycling are strong indicators of how well the built environment supports physical activity, which in turn influences mental health. One approach of quantifying how well the built environment supports physical activity is to develop a walkability index.

Walkability Index

According to Southworth (2005, p. 248) walkability refers to:

"the extent to which the built environment supports and encourages walking by providing for pedestrian comfort and safety, connecting people with different destinations within a reasonable amount of time and effort, and offering visual interest in journeys throughout the network."

A method currently being deployed in health research to measure the walkability of an area is to construct a composite measure called a "walkability index" using Geographic Information Systems (GIS). A walkability index measures the degree to which an area provides an opportunity for walking by taking into account the relationship between various characteristics of the built environment (Brownson, Hoehner, Day, Forsyth, & Sallis, 2009). The last decade has seen an increase in the number of composite indices being constructed, each differing in terms of spatial scale and components. Net residential density, street connectivity and land use mix are the three core components that form the basis of a vast majority of walkability indices (Stockton et al., 2016). Most studies that have developed walkability indices have linked walkability to physical activity and weight (L. Frank et al., 2009; Stockton et al., 2016; Van Holle et al., 2014). Only a few have linked walkability or the built environment to mental health (Gary W Evans, 2003; Halpern, 2014; Melis, Gelormino, Marra, Ferracin, & Costa, 2015). In New Zealand, only a few studies have developed walkability indices. However, many have acknowledged the importance of these indices in helping us to understand the influence of the built environment on our health (J Pearce, Hiscock, Blakely, & Witten, 2008).

2.3 Depression in adolescence

Adolescence

According to the World Health Organisation (WHO), an adolescent is any person aged between 10 and 19 (Miller, 1969). In this thesis, adolescents will refer to secondary school students aged 12 to 18 years old due to this being the age range covered by the Youth'12 National Youth Health Survey, the primary data source for this study.

Adolescence marks the transition from childhood to adulthood. It is a period of both physical and psychological changes, often characterised by emotional instability, and physical and mental development (Thapar et al., 2012). These instabilities and developments usually trigger prolonged and intense periods of stress, often resulting in feelings of depression. Prolonged and intense periods of stress may be an indication that an individual has a severe disorder (Sadock & Ruiz, 2015).

Depression

According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), depression falls under the "mood disorder" category. Depression causes various severe symptoms that affect how individuals feel, think, and handle daily activities (Egede & Ellis, 2010). "Depressive disorders include disruptive mood dysregulation disorder, major depressive disorder (including major depressive episode), persistent depressive disorder (dysthymia), premenstrual dysphoric disorder, substance/medication-induced depressive disorder, depressive disorder due to another medical condition, other specified depressive disorder, and unspecified depressive disorder" (Kupfer, 2014).

Depression in adolescents is often overlooked. This is potentially due to the constantly shifting symptoms in adolescents (Thapar et al., 2012). Other instances of when adolescent depression can often be missed include when the issues being presented are unknown physical symptoms, eating disorders, anxiety, poor attendance and performance at school, substance abuse, or behavioural problems (Thapar et al., 2012).

Epidemiology of depression

According to annual results from the New Zealand Health Survey (NZHS), the prevalence rate for diagnosed depression in adults in 16.7%, which is an estimated 640,000 adults. The same survey showed that there is an increasing number of adolescents experiencing psychological distress. Psychological distress is defined as "high or very high probability of anxiety or depressive disorder"(Ministry of Health, 2017). The percentage of 15 – 24-year-olds struggling with psychological distress has slowly increased from 6.4% (CI: 5.1% - 8.1%) in 2006/07 to 11.7% (CI: 9.8% - 13.9%) in 2016/17. Among indigenous populations, the adjusted rate ratio of 1.03[1] shows that Māori are 1.3 times more likely than non-Māori to have diagnosed depression after adjusting for differences in sex and age (Ministry of Health, 2017). These results indicate that mental health disparities are prevalent between Māori and non-Māori, similar to results from other indigenous populations worldwide (Kisely et al., 2017). Overall, this shows that psychosocial and cultural factors may be playing a significant role in the prevalence of depression.

In addition to disparities between different cultural groups, the literature shows that there is a disparity in depression prevalence rates within the sexes. According to Sadock and Ruiz (2015), females have a prevalence rate of 2- 3 times that of males. The New Zealand results from the Youth'12 National Youth Health Survey showed that adolescent females (16.2% CI14.6 – 17.8) [2]have a higher prevalence of significant depressive symptoms than males (8.6 % CI 7.5 – 9.7)[2](Clark et al., 2014). According to Bouma, Ormel, Verhulst, and Oldehinkel (2008), this difference in outcomes may be partially attributed to changes in hormone levels. Another study by Mezulis, Funasaki, Charbonneau, and Hyde (2010) shows a stronger relationship between stressful life events and depression over time for young females than for males. These two studies suggest that both biological and psychological factors influence the development of depression in adolescents.

[2] 95%CI = 95% confidence interval

Chapter 3: Literature review

The purpose of the current research is to examine the possible relationship between walkability (as a potential indicator of the built environment) and depression (as an indicator of mental health) in adolescents based in the Wellington Region. This chapter critically reviews the validity of the existing research on the built environment and other factors that potentially explain depression in adolescents. This chapter also highlights inconsistencies, methodological limitations, and gaps in the literature that demand further study. The research reviewed here is mostly from peer-reviewed journals relating to the built environment, natural environment, mental illness, and depression. Relevant literature has been identified using large citation databases such as Medline and Web of Science, and through Google Scholar. Search terms included but were not limited to"neighbourhood"; "built environment"; "walkability"; "walking"; "mental health"; "depression" and "adolescents".

3.1 Conceptual framework

The socioecological framework was developed to help understand the individual compositional characteristics of an individual (i.e. age, sex, ethnicity) and the contextual (social, economic, cultural and political) environment in which an individual lives and how they influence their health (Stokols, 1996).

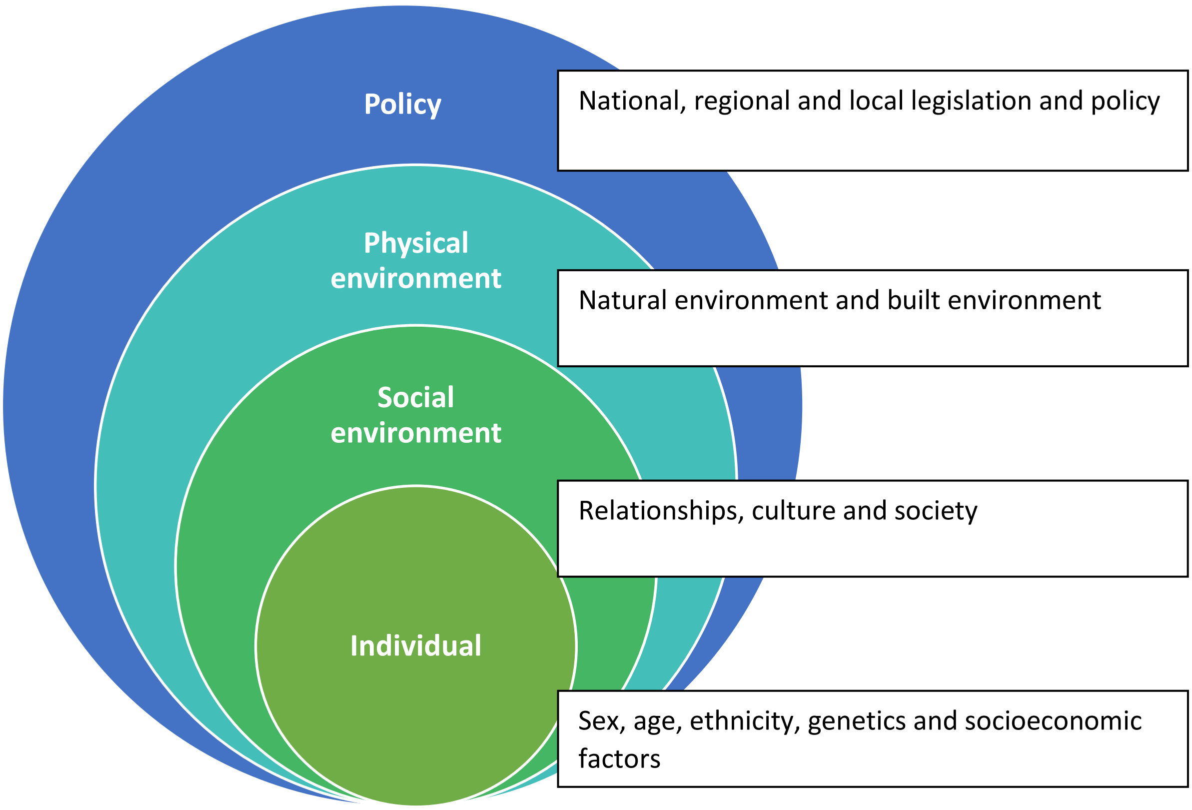


Figure 3. A socioecological model of factors influencing mental health – adapted from Johnson, Kirk, Rosenblum, and Muzik (2015)

The framework recognises that individuals are affected by multiple factors, which have direct and indirect influences on health outcomes. Overall, the socioecological model is useful for understanding and identifying the complex associations and interactions in which the built environment influences mental health. The model (Figure 3) helps to provide a basis from which to guide the literature review by outlining the main factors (Individual, social environment, physical environment and policy) that influence the interactions and relationships between the built environment and depression in adolescents.

3.2 Individual-level factors

The following section of the literature review explored the impact of individual-level factors and their influenced on mental health. Individual-level factors are socio-demographic characteristics (age, sex, ethnicity, employment, income and genetics) which determine spatial variations in health outcomes (Collins, Ward, Snow, Kippen, & Judd, 2017).

Age

Age has been linked to changes in the prevalence of mental illness. A 5-year study using data from a 1990 sample of 2,031 U.S. adults and a 1985 sample of 809 Illinois adults by Mirowsky and Ross (1992), found that depression scores (based on the Centre for Epidemiological Studies' Depression Scale (CES-D) measure) reached their lowest levels in middle-aged and were at their highest in adults aged 80 years and older. The fall of depression scores in the early stages of adulthood and rise in old age mostly reflects developmental gains and setbacks in marriage, employment, and income. In later life, this rise is due to low personal control and physical impairment. Because many of these life-cycle events can be prevented, the association between age and depressive symptoms can be changed (Blazer, Burchett, Service, & George, 1991). A review of the relationship between depression and age by Jorm (2000), found that overall the literature showed no consistant findings. In addition to this, the author suggested that the potential reason for these inconsistancies could be lack of adjustment for risk factors that are more prevelant at different ages. One study that attempted to adjust for these risk factors across age, was a study of 2,215 participants from two cohort studies by Schaakxs et al. (2017). The study found that the prevalence of depresison risk factors differed widely across age groups. Results from this research indicated that childhood abuse, obesity, pain and number of chronic diseases in younger people were strong predictors of depression. While in older adults, low income was the strongest risk factor for depression. Overall the study found that while risk factors change with age, the relative risk between those risk factors and depression remains largely the same.

Sex

Several studies have found a sex difference in the prevalence of depressive disorders. Women, particularly during their reproductive years, have been shown to have a prevalence rate of up to twice that of men (Bebbington, 1996; Collins et al., 2017; Ronald C Kessler et al., 1994; Meltzer, Gill, Petticrew, & Hinds, 1995). In a study by Kessler, McGonagle, Zhao, and et al. (1994), women were approximately 66% more likely to be depressed in comparison to men. A survey in Britain showed a similar risk of depression for women (Meltzer et al., 1995). A New Zealand study by Sarah K. McKenzie, Collings, Jenkin, and River (2018), confirmed the sex difference between men and women, but found that in comparison to women, men experience greater social and mental functioning difficulties due to depression. In adolescents, one of the most robust epidemiological findings is the strong sex difference between boys and girls (Thapar et al., 2012). This finding is consistent across various methods of assessment, suggesting that the prevalence difference is not due to help-seeking or reporting. Adolescent depression is shown to be very closely tied to hormonal changes in females, suggesting that there is a link between depression and changes in androgen and oestrogen caused by puberty (Angold, Costello, Erkanli, & Worthman, 1999). Puberty alone does not explain this sex difference. Animal research by Hyde, Mezulis, and Abramson (2008), found that an increase in oestrogen increased the stress response in the prefrontal cortex. Therefore, suggesting that the differences between boys and girls after puberty are due to hormone-induced stress sensitivity and increased exposure to stressors in females.

A recent meta-analysis on sex differences in depression found evidence of a sex difference in major depression. It found that females have a higher prevalence than males. The study also found that the sex difference peaks in adolescence, with the gap emerging earlier than previously believed (OR = 2.37 at age 12) (Salk, Hyde, & Abramson, 2017). In New Zealand, research findings from the Youth'12 National Youth Health Survey showed that regardless of the method used to measure depression, females had a higher prevalence of significant depressive symptoms, lower emotional well-being and were more likely to have attempted suicide in the 12 months prior to the survey (Adolescent Health Research, 2013). Figure 4 shows that these findings were consistent across all years of the survey.

Have good emotional wellbeing[1]		2007		2012	
		n (N)	% 95% CI	n (N)	% 95% CI
Total		6,804 (8,679)	78.5 77.4 - 79.6	6,314 (8,286)	76.2 74.8 - 77.5
By sex	Male	3,917 (4,656)	84.2 83.1 - 85.3	3,076 (3,746)	82.1 80.9 - 83.3
	Female	2,887 (4,023)	71.9 70.5 - 73.4	3,236 (4,538)	71.3 69.3 - 73.2

Significant depressive symptoms[2]		2001		2007		2012	
		n (N)	% 95% CI	n (N)	% 95% CI	n (N)	% 95% CI
Total		1,139 (9,247)	12.4 11.5 - 13.3	910 (8,571)	10.6 9.7 - 11.4	1,045 (8,182)	12.8 11.6 - 13.9
By sex	Male	382 (4,237)	9.1 8.1 - 10.1	319 (4,589)	6.9 6.3 - 7.6	316 (3,676)	8.6 7.5 - 9.7
	Female	757 (5,010)	15.3 14.1 - 16.4	591 (3,982)	14.7 13.7 - 15.8	728 (4,504)	16.2 14.6 - 17.8

Students who have attempted suicide during the last 12 months[3]		2007		2012	
		n (N)	% 95% CI	n (N)	% 95% CI
Total		413 (8,715)	4.7 4.1 - 5.3	378 (8,325)	4.5 3.8 - 5.2
By sex	Male	138 (4,666)	2.9 2.4 - 3.5	93 (3,769)	2.4 1.8 - 3.0
	Female	275 (4,049)	6.7 5.9 - 7.5	284 (4,554)	6.2 5.2 - 7.3

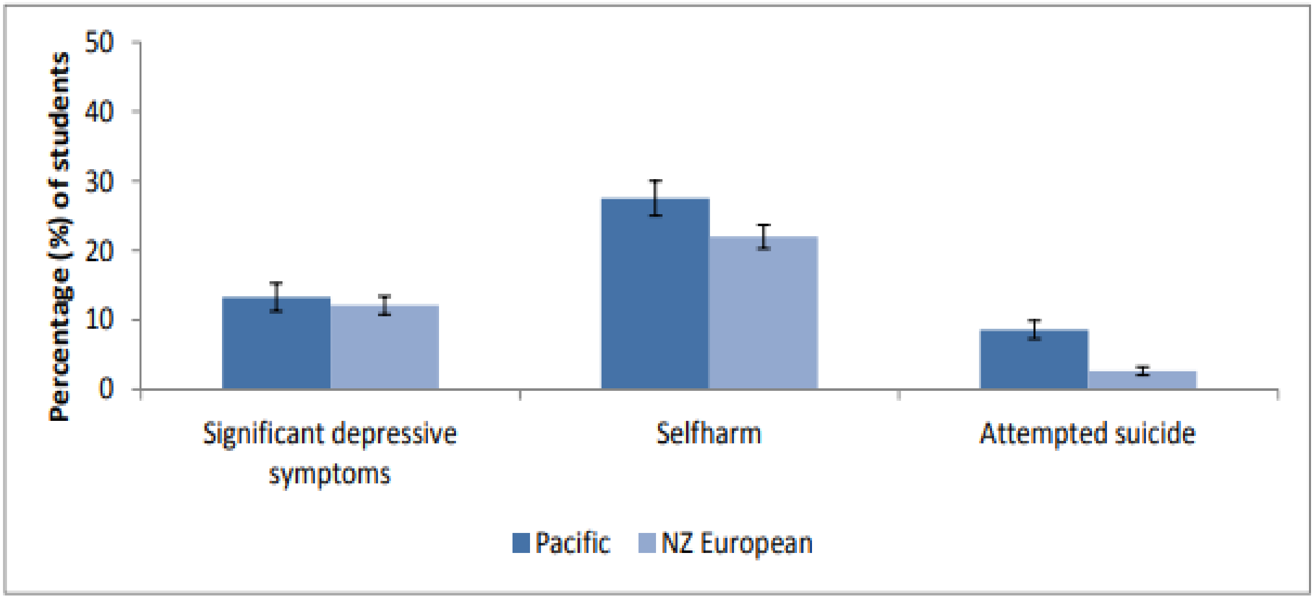
Notes:
1. Defined as a WHO-5 wellbeing score of ≥13. Not measured in 2001.
2. Determined using the Reynolds Adolescent Depression Scale – Short Form, as described at the beginning of this section.
3. In 2001, only students who reported that they had thought about attempting suicide were asked if they had made a suicide attempt. Consequently the 2001 results are not strictly comparable to those from 2007 and 2012 and are therefore not reported here.

Source: Adolescent Health Research (2013)

Figure 4. Emotional well-being comparisons 2001 - 2012

Ethnicity

The literature on the relationship between ethnicity/ race and depression is extremely limited, with a majority of studies based in the USA. Previous research by Riolo, Nguyen, Greden, and King (2005) showed that the prevalence of major depressive disorder was significantly ($p = 0.001$) higher in White Americans in comparison to all other ethnic groups (African Americans and Mexican Americans). In New Zealand, Māori and Pacific people have a higher prevalence of depressive disorder than those in the “Other” ethnic group (Elisabeth Wells et al., 2006). These results are also supported by results from the Youth2012’ National Youth Health Survey, which found that 14% of Māori secondary school students had significant depressive symptoms. While Pacific students were shown to have a similar prevalence of depressive symptoms to New Zealand European students, they were more likely to report self-harm and approximately three times more likely to have attempted suicide in the 12 months preceding the survey than European students (Figure 5) (Clark et al., 2014). These findings may be due to Pacific and Māori students being less likely to engage with mental health services compared to New Zealand European students (Tiatia-Seath, 2014).



Source: Adolescent Health Research (2013)

Figure 5. Emotional well-being of Pacific and New Zealand European students in 2012 Clark et al. (2014)

Socioeconomic status

In a household study of residents aged 16 and over, between 2003 and 2004, finding showed that the prevalence of mental disorders was higher for disadvantaged people, whether measured by educational qualification, household income or deprivation (Elisabeth Wells et al., 2006). From the literature, it is also clear that there are close links between education, income, deprivation and mental health disorders and they all interact in a negative feedback cycle. Mental health disorders lead to unemployment and reduced income, which in turn leads to poverty, a major risk factor for developing a mental health disorder.

In a New Zealand study by Sarah Kirsten Mckenzie, Carter, Blakely, and Collings (2010), the authors explored the relationship between socioeconomic status and psychological distress during childhood. They found that study participants from the lowest childhood socioeconomic backgrounds had greater likelihoods (35% more) of reporting high to very high psychological distress in comparison to those with higher childhood socioeconomic backgrounds. Additionally, the study found that 77% of the association between childhood socioeconomic status and psychological distress in adulthood is explained by adult socioeconomic status. In contrast, the study by Poulton et al. (2002), found that depression in adulthood is not related to low socioeconomic status in childhood.

In another New Zealand by Read (2010), of approximately 15,000 families, the author explored the relationship between asset wealth (home ownership and savings) and psychological distress. Those in the highest wealth quintile were three times less likely to report high psychological distress than those in the lowest wealth quintile. Even after controlling for confounders such as sex, age, health status and income, the difference remained statistically significant (OR= 3.06, 95% CI 2.68 to 3.50) (Read, 2010). In adolescents, the findings presented by the Youth'12 National Youth Health Survey, higher levels of household poverty were significant risk factors for depression ($P \leq .05$) (Denny, Fleming, Clark, & Wall, 2004).

3.3 The social environment – indirect influences

Numerous indirect pathways may influence how the built environment affects mental health. In this study, the following psychosocial processes will be explored; personal control, helplessness and social support.

Personal control and helplessness

Personal control refers to an individual's belief about the degree to which he or she can master, control and shape events in their life and that of their community (Ross & Sastry, 1999). The opposite of this is a sense of helplessness, which is expressed when an individual is exposed to an uncontrollable stimulus (e.g. traffic noise)(Abramson, Seligman, & Teasdale, 1978). Research has shown that helplessness is associated with depression and anxiety, both of which influence an individual's physical and mental well-being (Nolen-Hoeksema, Girgus, & Seligman, 1992; Nowicka-Sauer et al., 2017). Significantly, some studies have highlighted that helplessness, may be more prominent in individuals from vulnerable population groups (Broman, Mavaddat, & Hsu, 2000; Cheung & Snowden, 1990; Landry, Gifford, Milfont, Weeks, & Arnocky, 2018). Exposure to noise, crowding and unpleasant scents have been shown to cause helplessness in people (Campagna, 2016; Riedel et al., 2018). Research by Gary W Evans and Stecker (2004) found a significant association between residential crowding and indices of psychological distress and learned helplessness. These results were consistent in two different samples of elementary school children. In terms of young people, numerous studies support the notion that there is a relationship between helplessness and depression in youth (Gladstone, Kaslow, Seeley, & Lewinsohn, 1997; Joiner Jr & Wagner, 1995). Overall, these results indicate that while helplessness appears to be an important factor that influences mental health, it is not directly related to depressive symptoms. Instead, helplessness is related to increased stress, which in turn results in increased depressive symptoms.

Social Support

Social support is another pathway that has been shown to link the built environment and mental health. Numerous cross-sectional, prospective and intervention studies have concluded that there are a multitude of ways in which the built environment can influence the development of socially supportive environments (Brown et al., 2008; Elisabeth Wells et al., 2006; Yang & Matthews, 2010). Evidence from various studies has shown that crowded environments can reduce an individual's ability to form and maintain socially supportive relationships (Gary W. Evans & Lepore, 1993; Pepin, Muckle, Moisan, Forget-Dubois, & Riva, 2018; van Ginneken, Sutherland, & Molleman, 2017). A recent study by Firdaus (2017), which explored the contextual risk factors of mental well-being in older adults found a similar effect, with results from the study indicating that overcrowding was the most critical risk factor for poor mental health. In general, overcrowding reduces both physical and emotional space, interfering with an individual's ability to form socially supportive relationships within and outside of the household. For vulnerable populations (i.e. racial or ethnic minorities, older adults, children, people living with disabilities, low socioeconomic status groups, people living in rural areas) in particular this inability to form socially supportive relationships increases feelings of loneliness, which in turn increases stress levels, contributing to a decrease in mental health (Firdaus, 2017; Waisel, 2013).

While the stress-related health effects of traffic noise in relation to cardiovascular, respiratory and metabolic effects have been explored intensively, findings regarding an association between traffic noise and social support have been inconsistent (Beutel et al., 2016; Heidemann et al., 2014; Niemann, Maschke, & Hecht, 2005; Stansfeld, Haines, Burr, Berry, & Lercher, 2000). The most notable study was by Hart and Parkhurst (2011), who showed that individuals living in streets with high traffic volume were less likely to know their neighbour in comparison to those who lived in quieter streets.

3.4 The physical environment – direct influences

The following section of the literature review outlines the direct effects of contextual features of the built environment on mental health.

Contextual factors are the characteristics of the built environment in which individuals live that help to determine spatial variations in health outcomes. Various authors have theorised that contextual factors have an influence on the development of mental health disorders. Aneshensel and Sucoff (1996) explored the neighbourhood context of the mental health of young people, while Klebanov, Brooks-Gunn, and Duncan (1994) asked whether neighbourhood poverty affects the mental health of mothers. According to these authors, contextual determinates can act be protective or risk factors. Authors Gable, Reis, and Elliot (2000) showed that an adverse event in an individual's life is more likely to trigger depression if the person lives in a deprived neighbourhood than if they reside in a wealthy neighbourhood.

Green space

The importance of green spaces has attracted significant interest over the past few years. Evidence of this is supported by United Nation's member states committing to providing universal access to "safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities" by 2030.

In this review of the published literature on urban green space and depression/anxiety, green space is defined as any "green spaces", "public open spaces", "parks" or "reserves" in an urban locale. Previously research around urban green space has focused on the characteristics that encourage its use (e.g., access, attractiveness, safety, available facilities and quality) (A. C. K. Lee, Jordan, & Horsley, 2015). However, such an approach assumes that one variable has a direct influence on the use of urban green space, but the relationship is much more complex and dependent on other factors. Authors such A. C. K. Lee et al. (2015), suggest that the functionality of urban green space (as a location for exercise and social activities), not its characteristics are what translates to its benefits.

Green space plays numerous roles in urban settings. It acts as a location for cultural, recreational and social activities, has environmental benefits and has an impact on feelings of social safety and overall health. However, only a few studies have explored the relationship between urban green space and mental health at a population level. A Dutch study by De Vries, Verheij, Groenewegen, and Spreeuwenberg (2003) found that "In a greener environment people report fewer symptoms and have better perceived general health" which also includes perceptions of mental health. The effect was only found in the middle range of urbanity, which is an indicator of household density (households per square km) commonly used in the Netherlands. The data was categorised from very strongly urban (1) to nonurban (5). These results illustrate that the level of green space is merely an indicator of urbanity. A study by De Vries et al. (2003) suggests that the relationship between green space and health can be explained by the same mechanisms that explain the relationship between health and urbanisation. Numerous studies have found a reduction in depression after spending time in nature (Berman et al., 2012; McCaffrey, Hanson, & McCaffrey, 2010). Research conducted by Beyer et al. (2014), found that there was a significant relationship between higher levels of green space and lower levels of depression, anxiety and stress, even after controlling for age, ethnicity and marital status (in a rural environment). This study is one of only a few studies to consider the relationship between green space and mental health in a non-urban locale.

Research has indicated a beneficial association between green space and emotional and behaviour difficulties in adolescents. However, a systematic review conducted by Vanaken and Danckaerts (2018) shows that there is limited evidence supporting an association with depressive symptoms. A cross-sectional study by Huynh, Craig, Janssen, and Pickett (2013) based on the Canadian 2009/10 Health Behaviour in School-aged Children Survey found no strong relationship between natural public space within a 5000m buffer of the school area and positive emotional well-being (self-reported measure). Similarly, a study that explored the association between well-being and the use of different types of green space in adolescents in Singapore found that neither access nor the use of green space has a significant association with well-being (Saw, Lim, & Carrasco, 2015). In contrast to the previous two studies, findings from a study of 72 adolescents by Ward, Duncan, Jarden, and Stewart (2016) indicated that there was a positive association with green space and emotional well-being. The results indicated that for each increase in time spent in green space(1%) there was a 0.66 increase in life satisfaction score (a 5-item questionnaire derived from Hubener's Student Life Satisfaction Scale (Huebner, 1991). A limitation of this study, however, is that it did not include socioeconomic status as a confounder in comparison to the previously cited studies by Saw et al. (2015) and Huynh et al. (2013).

In New Zealand research on the built environment and health has focused mainly on the relationship between green space and physical activity. However, Nutsford, Pearson, and Kingham (2013) and Richardson, Pearce, Mitchell, and Kingham (2013) have both explored the relationship between green space and mental well-being. The latter found that increased greenness was related to a reduced risk of poor mental health. Nutsford et al. (2013), similarly found that being closer to useable urban green space was linked to a decrease in counts of anxiety/mood disorder treatment. While there appears to be a consensus around the evidence supporting the health benefits of urban green spaces, most of the evidence is based on self-reported health surveys and therefore tends to be qualitative or sourced from grey literature [3]. The lack of strong quantitative evidence may be due to a lack of national-level mental health data and the ability to quatify intangible health benefits, therefore resulting in an under-estimation of the prevalence of mental illness (A. C. Lee & Maheswaran, 2011).

The cause of such different results in adult and adolescent studies may lie in differences in the way in which both age ranges use, interaction and perceive green space. Adolescents, in comparison to adults, have a lack of control over where, when and how they choose to interact with green space, this is potentially due to adults influencing where they can go and where they can play. Additionally, while

[3] Documents produced outside of traditional channels such as reports, working papers, and government documents.

adults view green space as a location for gaining tranquillity, adolescents may view these areas as locations for play and socialising (Karsten, 2005).

Urbanisation and household crowding

Urbanisation has been shown to have a relationship with mental health. A Swedish study by Sundquist, Frank, and Sundquist (2004) examined the relationship between urbanisation, psychosis and depression. Results showed that after adjustment for individual, demographic and socioeconomic characteristics, there was an association between increased urbanisation and increased incidence rates of psychosis and depression. A study by Schweitzer and Su (1977), based in Brooklyn, New York compared age-specific rates of psychiatric admissions to population density. The study found that household or social contact had a statistically significant impact on admissions. Household contact was defined by two indicators. The first calculated the percentage of households with three or fewer people, while the second calculated the percentage of people living in households of less than or equal to 0.75 individuals per room. The study suggests that if population density does produce mental illness, then household contact is potentially the key mechanism driving the relationship. Other measures of density explore such as people or households per kilometre did not show such an association with mental illness

In addition to household contact, several previous studies have shown a relationship between mood disorders and poor social networks (Cheng, Chen, Chen, & Jenkins, 2000; Fridell, Öjehagen, & Träskman-Bendz, 1996; Hirschfeld et al., 2000). These studies suggest that social networks may also be another key mechanism that drives the relationship between urbanisation and mental health. Much of the research on crowding and mental health has attempted to discover direct links between household density and mental illness. In general, there is strong evidence supporting an association between higher levels of household crowding and increased levels of psychological distress in adults (Gary W Evans, 2003; Gomez-Jacinto & Hombrados-Mendieta, 2002; Lepore, Evans, & Schneider, 1991). The most widely cited of these studies is a large cross-sectional study in Chicago by Gove, Hughes, and Galle (1979) which revealed a strong relationship between crowding (persons per room) and poor mental health. While several authors have supported the strong evidence linking crowding to mental health, Smith, Smith, Kearns, and Abbott (1993) and Wilkinson (1999) pointed out that the relationship between household crowding and health was too multifaceted, as many confounding factors may be influencing it.

In New Zealand there is little evidence linking household crowding to mental health. Crowding has been previously linked to rental tenure, and being of Māori and Pacific ethnicity, low income and lack of qualifications, but very little attention has been given to its influence on psychological distress and mental health (Baker, Goodyear, Telfar Barnard, & Howden-Chapman, 2006). Additionally, the pathways by which household crowding influences mental health remain unclear. Previous research has suggested that loss of control or interpersonal interaction may be an underlying process that can cause poor mental health (Altman, 1975; Saegert, 1982).

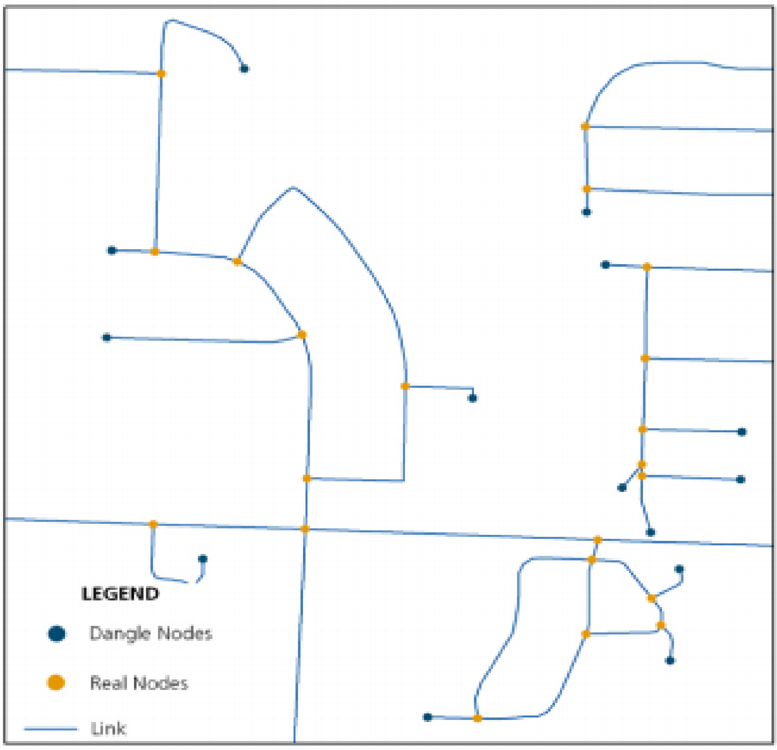
Environmental friendliness

Environmental friendliness refers to how attractive and friendly an area is and is an important measure in determining the walkability of an area. According to Brownson et al. (2009), there is a strong relationship between walkability, safety, aesthetics and presence of footpaths. Environmental friendliness can be measured in numerous ways; from air pollution and footpath width to perceived crime and speed limits.

In terms of safety, research has shown that perceived crime has an impact on physical activity, due to individuals feeling unsafe (Catlin, Simoes, & Brownson, 2003). This observation is supported by two other studies that examined the relationship between environmental friendliness and physical activity levels. Firstly, a study by Kneeshaw-Price et al. (2015) on the association between various measures of crime-related safety and children's' physical activity found that even after accounting for covariates, children living in areas with high levels of police-reported crime were less likely to be physically active. Likewise, Esteban-Cornejo et al. (2016) showed that parental perceptions of crime and traffic safety were all associated with active travel in adolescents. Therefore suggesting that all policy and environmental changes that affect the neighbourhood must account for the impact of crime and safety on the overall health and well-being of individuals in the neighbourhood.

Another aspect of environmental friendliness that has been linked to walkability is footpath width, which has been used as an environmental safety measure in numerous walkability indices. A study by M. L. Booth, Owen, Bauman, Clavisi, and Leslie (2000) found that perceiving footpaths as safe for walking was associated with a decrease in physical activity. In addition to footpath safety, another aspect of the pedestrian network that has been shown to influence active travel and subsequently mental health and well-being is intersection density. Intersection density is a measure of street connectivity, which refers to the density and directness of links in footpaths or road networks. A well-connected network has many short links and several intersections. As connectivity increases, the distances that individuals must travel decrease, increasing the number of possible routes. Overall, this allows for more direct travel between various locations, increasing the accessibility and resilience of the network

Many measures have been used to determine street connectivity. Dill (2005) explored the merits of various measures of connectivity for increasing walking and bicycling. These included: block length, block size, block density, intersection density, street density, pedestrian route directness and effective walking area. Of all the measures explored, intersection density (i.e. the number of intersections in an area) was found to have the largest effect on walking, use of public transport and driving (Ewing & Cervero, 2010). As intersection density increases, block size decreases. Smaller blocks make neighbourhoods more walkable, which can be measured by totalling the number of real nodes (Figure 6) in an area. A higher number of real nodes would indicate more intersections and therefore higher connectivity.



Source: Tresidder (2005)

Figure 6. An example of elements of connectivity

Higher connectivity increases the efficiency and ease of walking and cycling between places. Subsequently helping to improve health and prevent future depression.

Overall research has shown that an individual's negative perception of the community regarding crime, traffic safety, and appearance is associated with reduced physical activity. While a large majority of studies has supported the idea that neighbourhood safety has a statistically significant impact on walking and physical activity, others have found no statistically significant relationship. For instance, the results from a national sample of 2,912 women 40 years of age or older, showed that safety was not a significant barrier to physical activity and walking (King et al., 2000). Similarly, Giles-

Corti and Donovan (2002), in a study of 1,803 adults in Perth, Australia, found that the physical environment did not have a prominent role in influencing physical activity. The reason for these contrasting findings can be attributed to the variation in methodologies.

In addition to safety, the appeal of an environment in terms of the number of different services available has been shown to influence physical activity (Koohsari et al., 2015; Wei, Xiao, Wen, & Wei, 2016). A well-mixed land use supports and offers a wider range of services; therefore, shortening trip distances (Feng, Glass, Curriero, Stewart, & Schwartz, 2010). Mixed land use also provides higher visual variety and interest for pedestrians, making walking more attractive (Forsyth, Schmitz, Oakes, Zimmerman, & Koepp, 2006). A study by Li et al. (2008) found that a greater land use mix is associated with higher levels of walking because there is a greater number of destinations located with walking distance of a neighbourhood. A study conducted by (Miles et al., 2012) produced contrary results. Land-use diversity was not a predictor of depression symptoms, but the authors believed that measurement error was the cause of the difference between this study and other previous studies.

3.5 Developing a measure of the neighbourhood environment

This section of the literature review briefly evaluates the implications of using different methods to define the neighbourhood area.

One of the challenges that arise when developing a walkability index is defining the term “neighbourhood”. Generally, the term “neighbourhood” has been used to refer to an individual’s “residential environment” (Diez Roux, 2001). Diez Roux (2001) theorised that a “residential environment” has both physical and social features that are potentially related to health. Despite this loose definition of the neighbourhood environment, there is currently no universal definition regarding what the appropriate size of a neighbourhood should be. Presently, arbitrary areas are used as rough proxies for neighbourhood areas due to data being easily available at these levels. These are generally either administrative boundaries such as meshblocks, Census area units, or buffer zones from a specified point (K. M. Booth, Pinkston, & Poston, 2005; Diez Roux, 2001; Mujahid et al., 2008; Jamie Pearce, Witten, & Bartie, 2006). However, a limitation of these methods is that they do not necessarily represent areas in which individuals walk (Oliver, Schuurman, & Hall, 2007). Other studies have suggested using buffers instead of administrative boundaries as they more accurately approximate a maximum walking distance (Salze et al., 2011). However, this method is also likely to be inaccurate in locations with natural and built environment features such as rivers, lakes, railway lines, etc. For instance, an individual may live in an area that is mostly inaccessible, but the whole area is still used when calculating built environment measures.

The inconsistencies in results between studies exploring the influence of the built environment on health can be attributed to the use of different methods to define the neighbourhood area. Research has shown that the way in which the neighbourhood area is measured has important implications for research results. A study by Flowerdew, Manley, and Sabel (2008) found that analytical conclusions may differ significantly depending on the method used to aggregate data while Haynes, Ackloo, Sahota, McDonald, and Yao (2008) found that the different sizes and shapes of a neighbourhood area had minimal effect on the results.

The issues presented above are forms of an ecological fallacy known as the map area unit problem. According to Wong (2009), the essence of MAUP can be captured in the zonal and spatial effects. In terms of the scale effect, the same dataset can yield different analytical results depending on the size of units used (generally the more aggregation, the more pronounced the correlations are). The zonation effect is described as the difference in results caused by how the area of interest is divided, even at the same spatial scale. A possible solution is to analyse data at several different scales. The current research addresses the MAUP by measuring the influence of the built environment using an 800m (meters) Euclidean and Network buffer, then comparing the results. In addition to considerations about the different proxies for the neighbourhood area, it is important to also take resident perceptions of the neighbourhood area into account. An individual's subjective description of their neighbourhood can differ significantly to that of an academic (Hester, 1984). Residents tend to view neighbourhoods in terms of comfort and familiarity while academics and planners view neighbourhoods in terms of the number of people (Hester, 1984). However, such an undertaking would require a significant amount of researcher effort, time and money.

3.6 Conclusion

This literature review showed that there are a limited number of studies related to mental health and the built environment, especially in the New Zealand context. The literature suggests that the built environment is perhaps an important factor in the occurrence of mental health. Therefore, the ability to recognise and alter features of the built environment to support better practises and behaviours by adolescents can have significant benefits to long-term health outcomes, as adolescents are more susceptible to their built environments due to restricted mobility.

Overall, this review showed that there is a lack of consensus about how the built environment contributes to the occurrence of depression. Another shortfall is that many of the studies reviewed have not tailored their walkability indices to the study population. The limited number of New Zealand studies reviewed also shows that there is a gap in our knowledge of how the built environment affects our mental health. Therefore, our understanding of this relationship in adolescents is insufficient. Results from adult studies cannot be generalised to adolescents due to differences in how they interact with the built environment.

This chapter presents the methodological considerations of the current study. The first section presents an outline of the study area, with an overview of the population demographics. The research is undertaken in two phases. The first phase involves the development of measures of the built environment based on previous research outlined in the literature review. The second phase involves the construction of the walkability index.

4.1 Study area

This study was conducted in the Wellington Region of New Zealand. The Wellington Region is situated in the southern-most part of the North Island and is the location of the capital city of New Zealand, Wellington City.

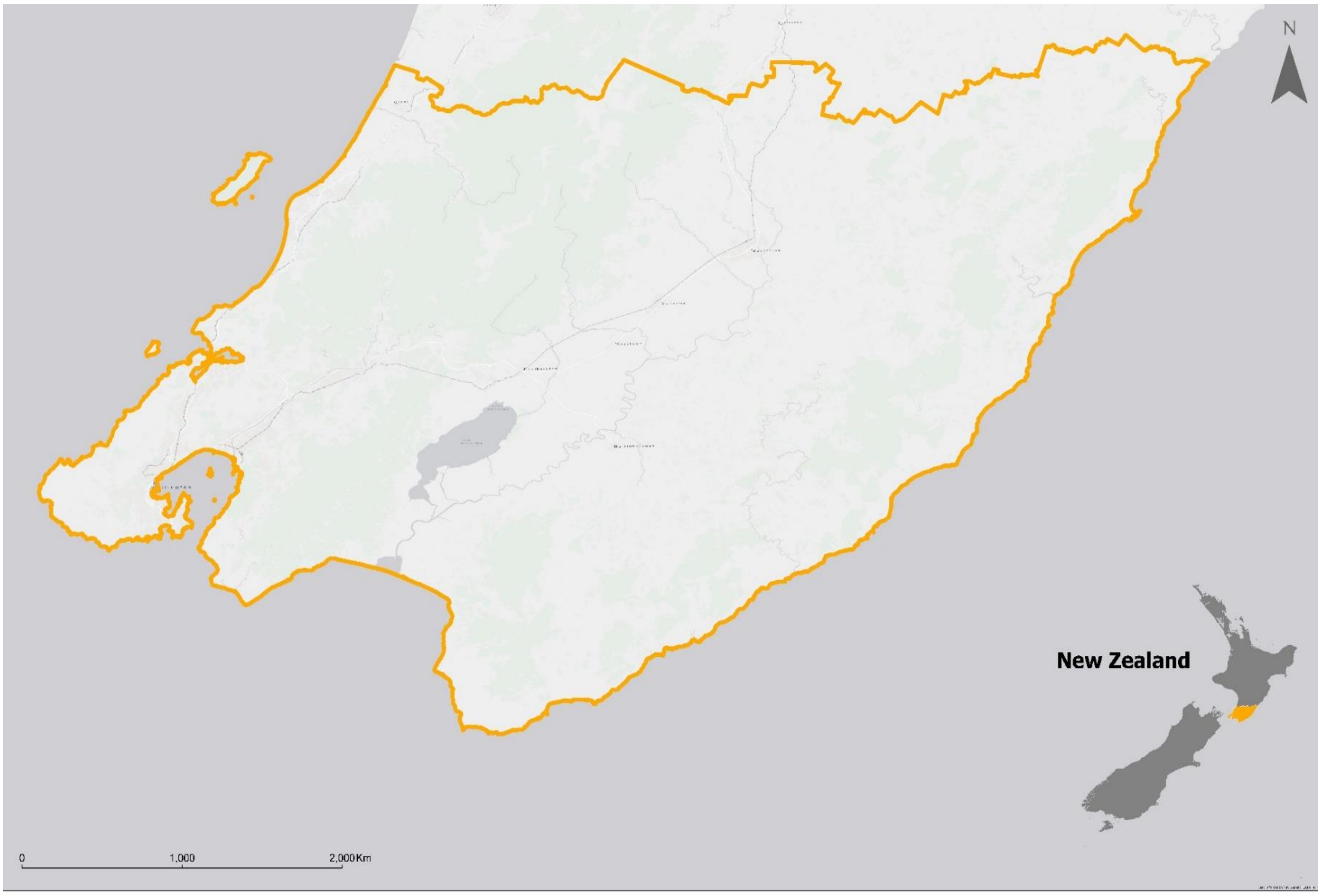


Figure 7. Map of the study area - Wellington Region

Population demographics

The Wellington Region has a current population of 513,900 and covers a region of 8,049 square kilometres (Statistics New Zealand, 2017). Over three-quarters of the 513,900 reside in the four cities at the south-western corner, Wellington city, Lower Hutt, Porirua and Kapiti. Adolescents between the ages of 12 and 24 make up approximately 34% of the total population in New Zealand, with about 11% of the total population of young people located in the Wellington Region (Statistics New Zealand, 2013). The Wellington Region was selected to test the association between walkability and adolescent depression for a number of reasons. Firstly, walking and cycling make up 25% of the region's daily trips, comparison to 14% nationally. Overall, the Wellington Region has lower levels of motor vehicle use and higher levels of active travel in comparison to the national average. Secondly, previous research by Hannah M. Badland et al. (2009) found Wellington City to have higher walkability scores than the three other major cities (i.e. North Shore, Waitakere, and Christchurch) in New Zealand. Overall, applying previously developed methodologies and comparing findings with previous research is important for validating previous research and contributing to the built environment research field.

4.2 Overview of data sources

This table shows a summary of the data used in this research and there source. In-depth information on data cleaning and preparation of each data source can be found in the relevant sections.

Table 1.Summary of data sources

Data	Source	Date
Health data	Youth'12 National Youth Health Survey - University of Auckland Adolescent Health Research Group	2012
New Zealand Census 2013	Statistics New Zealand	2013
National Road Centreline dataset (traffic volume)	New Zealand Transport Agency Open Data Portal	Sourced 1/4/2018
Land use data	Open Street Maps	Sourced 1/1/2018
NDVI data	USGS Earth Explorer	Sourced 1/1/2018
Meshblock boundaries	2013 New Zealand Census, Statistics New Zealand	2013

A measure of depression – Youth'12 National Youth Health Survey

A wide range of indicators based on self-reporting and official diagnoses have previously been used as measures of mental health. In New Zealand, researchers have made use of data from the Kessler Scale collected by the NZHS and treatment data from the Programme for the Integration of Mental Health Data (PRIMHD). The current research used data on the Reynolds Adolescent Depression Scale (RADS) obtained from the Youth'12 National Youth Health Survey, a survey exploring the health and well-being of 8,500 secondary school students aged from 12 to 18 years (Adolescent Health Research, 2013). The Youth'12 National Youth Health Survey was selected over the PRIMHD data source, as it is more comprehensive and tailored towards adolescents. The sampling method used to select students in the survey involved randomly selecting 125 schools that met the selection benchmarks and inviting them to participate in the survey. From the schools with more than 150 Year 9 to13 students 20% were randomly selected, while for schools with less than 150 Year 9 to 13 students, 30 students were randomly selected.

The RADS is a self-report measure of the severity of depressive symptoms made up of 30-items. It consists of a four-point response arrangement that evaluates the frequency of occurrences of item-specific symptoms (Reynolds, 2010). While this scale is not a formal diagnosis of depression, it does allow for the identification of clinical significant depressive symptoms in adolescents (Reynolds, 2010).

To obtain meshblock information, each student was asked to allow their address to be entered into geo-coding software that obtained their Census meshblock number for their usual place of residence. Students who lived in more than one house were asked to provide address information for the home they spent the most time in. Although this data cannot be attributed to an address point, it does contain information on the meshblock number of each student's usual residence. In addition to data on the RADS, demographic information regarding age, sex and ethnicity is associated with these cases.

The following contextual data was also obtained:

Urban/rural classification

Every student's meshblock was classified as either a main urban, minor urban or rural area. The Statistics New Zealand classification states that main urban areas have a population of approximatetly 10,000, while populations in minor urban areas are between 1000 and 9999 people, and rural areas have a population of fewer than 1000 people (Statistics New Zealand, 2019).

In addition to the measure above, two measures of deprivation were used in this analysis.

New Zealand Deprivation Index

The New Zealand 2013 Deprivation Index (NZDep2013) is a measure of nine aspects of neighbourhood deprivation (i.e rates of no access to internet, unemployment, recipient of state-funded benefits, household income, home ownership, lack of educational qualifications, single-parent families, overcrowding, and no access to a car) derived from the 2013 New Zealand Census data.

Household socioeconomic deprivation

Authors Denny et al. (2016) have constructed a measure of household poverty based on nine indicators of household socioeconomic deprivation (no car; no phone; no computer; their parent/s worry about not having enough money for food; more than two people sharing a bedroom; no holidays with their families; moving home more than twice that year; garages or living rooms used as bedrooms; and, no parent at home with employment). The measure included data from the 2013 New Zealand Census, previous questionnaires from the Youth'12 National Youth Health Survey and including items from the Health Behaviour in School-Aged Children (HBSC) family affluence scale. The household poverty measure developed by Denny et al. (2016) differs from the New Zealand deprivation index as it uses additional data sources and accounts for the fact that adolescents often have little income, are unemployed, are dependent on their caregivers and have not completed their education. During the analysis conducted in Chapter Six, only the household poverty measure developed by Denny et al. (2016) is used during the analysis due to autocorrelation between the two indices.

Validating the index - New Zealand Census 2013

Active travel data from the 2013 Census was obtained from Statistics New Zealand and used to validate the walkability indices and test the association between walkability and active travel to work in the Wellington Region. This section presents the selected variables and potential confounders. Each of the demographic and socioeconomic variables have been calculated as proportions of the total population at the meshblock level.

Main means of active travel to and from work

An 'Active travel' count variable was created by combing the number of participates who walked, jogged or cycled to and from work, using the "Main mode of transport to work on Census day" variables.

Age, Sex, and Ethnicity

The Census meshblock dataset provides the count of the usually resident population by age groups in five categories. For this analysis, only four age groups were selected (15-29, 30-44, 45-54 and 55-64-year-olds), as they were a clearer representation of the working age population. These variables were calculated by dividing the total count of each age group by the total usually resident population. Sex and ethnicity were calculated similarly. Instead of the six ethnic groups presented in the Census, this research only used four categories, Māori, Pacific, Asian and European/Other.

Education

The "highest qualification, for the Census usually resident population count aged 15 years and over" variable contains 12 variables related to the highest qualification gained by individuals. It was restricted to the age groups (15-64) defined above. For this analysis, these categories were aggregated into five categories: no high-school qualification, a high-school qualification, a post-high school diploma/ certificate, an undergraduate degree and a postgraduate degree. The proportion of each of the groups stated was calculated by dividing the total count for each qualification group by total people stated, this was repeated for all the variables presented below.

Number of vehicles per household

The number of vehicles per household was included as previous research had shown that car ownership has a negative influence on active travel (Fairnie, Wilby, & Saunders, 2016). The Census variable "number of vehicles for households in occupied private dwellings" is classified into four main categories; no vehicle, one vehicle, two vehicles and three or more vehicles. All four variables were used in the analysis, and the proportion of each of these groups of vehicles per household was calculated as a representation of individual car ownership.

Household Income

Household income has been shown to influence an individual's ability to purchase forms of transport that discourage active travel(McCarthy, Delbosc, Currie, & Molloy, 2017). The Census classifies the total household income in occupied private dwellings into six groups: 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. The NZ$20,000 or less income group was excluded from the investigation as the focus of this analysis is on individuals who commute to work and this income group is less than a working income in a year (Donnellan, 2016). The proportions of each income group were calculated as a representation of household income.

4.3 Overview of methods

This analysis was performed using meshblocks located in "urban areas" as defined by the Statistics New Zealand urban/rural profile; the Wellington Region has an average population size of 96 people per meshblock. This measure was taken due to the unique challenges that rural areas present when measuring objective measures of the built environment. For instance, rural areas have smaller populations distributed over larger geographic areas, which means that when calculating measures such as household density and intersection density, sparsely populated rural meshblocks will demonstrate a decreased intersection and household density. Overall, meshblocks were selected as the administrative area, as they are small enough to be statistically robust while also conveying a sense of neighbourhood.

Software

Spatial analysis was conducted using Esri ArcGIS 10.2 and QGIS software, while statistical analysis was complete in R studio (ArcGis, 2014; Qgis Development Team, 2016; RStudio Team, 2015).

A measure of the neighbourhood environment

Based on a review of the literature, the current study used administratively and buffered (Network and Eucleadian) defined areas to represent a neighbourhood. Administratively defined areas are aggregations of geographic data that partition New Zealand into different sub-units. The five most commonly used aggregations are: meshblocks, area units, territorial authorities (districts), regional councils and aggregated regional councils (Grimes, Maré, Morten, & Maré). Buffer defined areas are areas measured a specific distance outwardly in all directions from a point, line or area.

The meshblocks were used as an initial starting point from which to define the neighbourhood area. A total of 326 meshblocks with a zero population were excluded from the analysis, as the aim of this research was to measure the built environment around the theoretical location of the survey participant's homes. A population-weighted centroid (PWC), which represents the spatial distribution of the population in each meshblock was then calculated for each meshblock to determine the point from which the neighbourhood buffer would be measured. A buffer of 800m was used as previous research has indicated that this approximates the distance that individuals can walk or cycle to within 10 minutes (Diez Roux, 2001). Also, a similar New Zealand based study had used this same distance as it represented a reasonable walking distance to community facilities (Mavoa, Witten, Pearce, & Day, 2009). While there is significant research examining walkability with circular and network buffers, very few have compared both. This research seeks to examine the influence of dwelling density, intersection density, land-use mix, NDVI and average traffic volume on adolescent depression using an 800m Euclidean and network buffer.

Figure 8. Example of Euclidean buffer around a population-weighted centroid

4.4 Developing a Euclidean-based walkability index

In this section of the methodology describes the calculation of the following measures of dwelling density, land-use mix, intersection density, NDVI and average traffic volume were calculated using an 800m Euclidean buffer.

Dwelling density

The term "density" can be measured in terms of various aspects such as population, housing or employment. The term refers to the amount of activity found in an area. In the current study, density is measured using net residential density, which excludes other land uses, as gross density is calculated for all land uses including non-urban land uses and areas where individuals do not live. According to Feng et al. (2010), an area of high density suggests that an area is highly developed, which reduces the travel distances between departure and destination sites, therefore decreasing the reliance on motor vehicles. Therefore dwelling density is considered as a vital measure for developing a walkability index as it is highly correlated with walking. Dwelling density was calculated using dwelling data from the 2013 NZ Census and land-use data from Open Street Maps.

$$\textbf{Dwelling density} = \frac{\text{Count of private dwellings in each meshblock}}{\text{Total residential area of land in each meshblock}}$$

As shown in Figure 9, the densest areas in Wellington City are those adjacent to the city centre, while meshblocks with parks and hills have low dwelling density. Lower Hutt City has the highest dwelling densities in comparison to other cities in the Wellington Region. In particular, areas outside of the Lower Hutt city centre, such as Eastbourne, have a high dwelling density due to a large proportion of the land being used for residential purposes.

In Masterton, walkability appears to be the highest in the areas outside of the centre, this pattern can also be seen in Featherstone, Greytown and Carterton. However, in Martinborough, the most walkable areas are those located in the south east of the town (Figure 10).

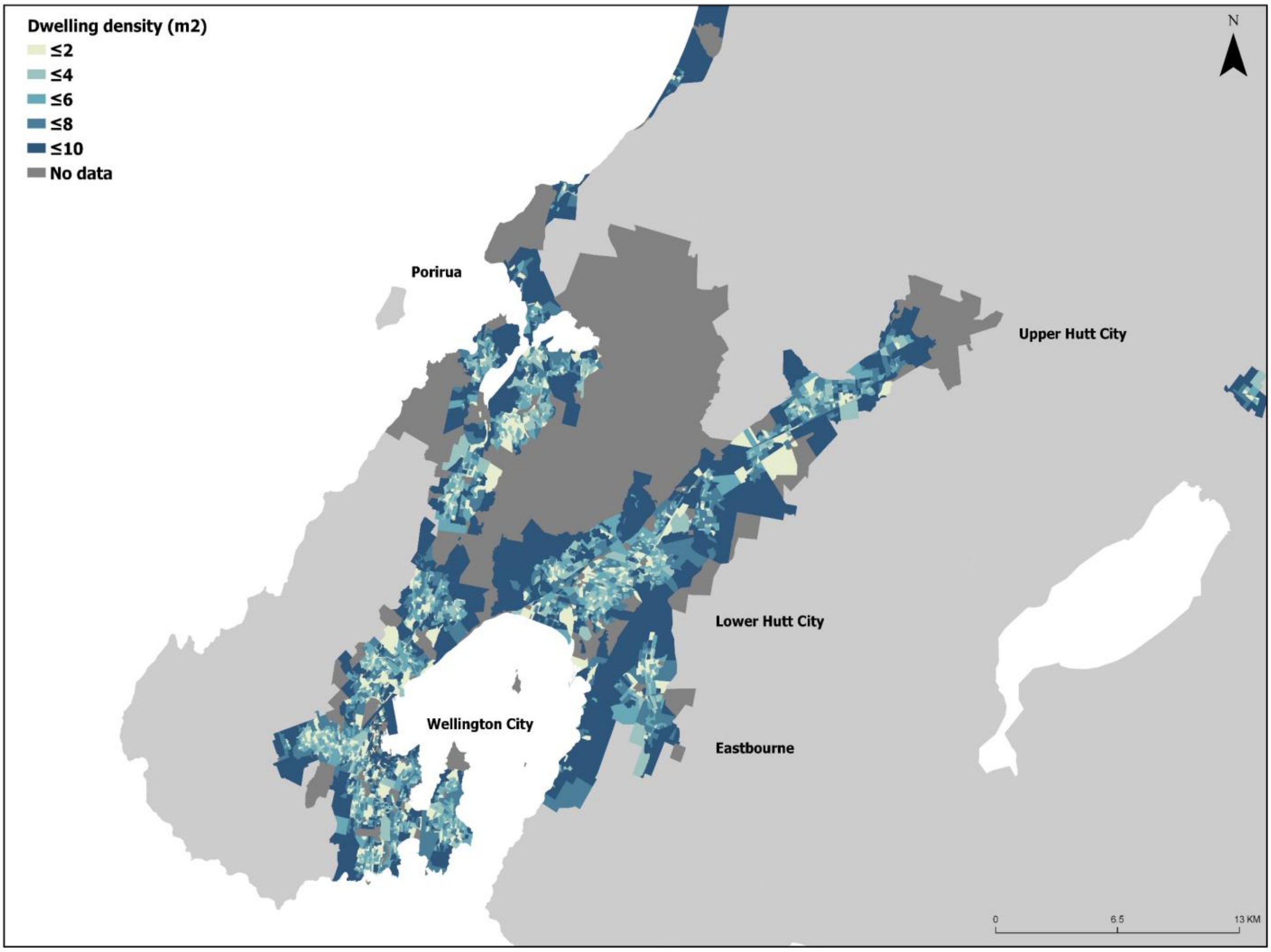


Figure 9. Dwelling density map of Wellington Region - Dwellings per m2 (Euclidean) (Map1)

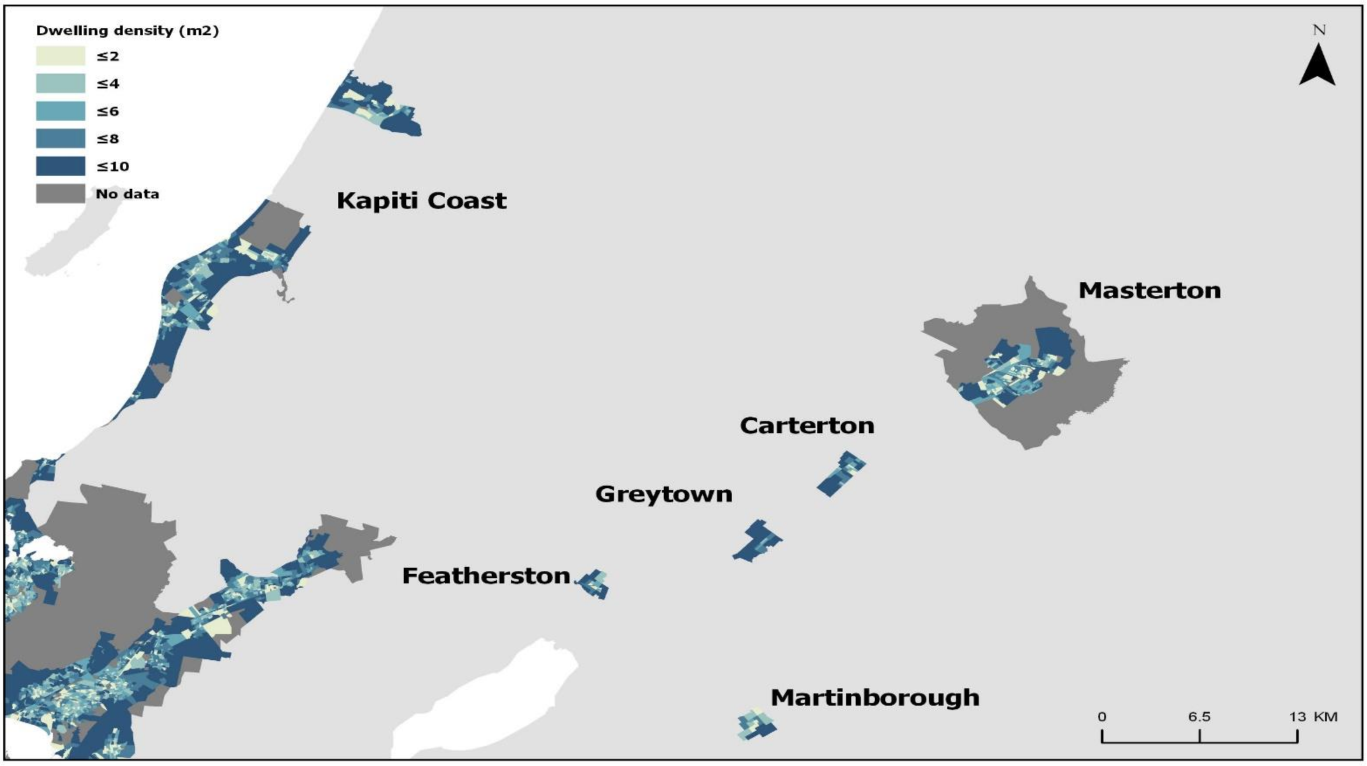


Figure 10. Dwelling density map of Wellington Region - Dwellings per m2 (Euclidean) (Map2)

Land-use mix

Land-use that is mixed refers to land that supports a wide range of services within proximity of each other (Mavoa et al., 2018). It has been cited as being conducive to active travel. This type of land-use not only makes walking more attractive but it also provides "higher visual variety and interest for pedestrians" (Forsyth et al., 2006). The land-use mix variable was calculated using land-use data obtained from Open Street Maps. Six categories were selected: residential, retail, commercial, industrial, green space and other. The land-use mix (LUM) was then calculated using the entropy index introduced by Cervero (1989), employed by L. D. Frank and Pivo (1994) using GIS techniques and standardised by Maria Kockelman (1997). It is the most commonly used and widely accepted index for representing the land-use mix. In 2013, research by Song, Merlin, and Rodriguez (2013) comparing characteristics of various land use diversity indices confirmed that the LUM entropy index was the most efficient.

The intensity of land-use mix in each meshblock area was determined using the following equation:

$$\sum_j \boldsymbol{P_J} \times \frac{\ln(\boldsymbol{pj})}{\ln(\boldsymbol{J})}$$

Where,

P_j = the proportion of the total land area of the j^{th} land-use category in the meshblock being analysed

J = total land uses considered in the study area

Since the entropy is normalised using natural logarithm of the number land uses, its value lies between zero and one. Therefore, homogenous meshblocks will have values close to zero, while meshblock with a mix of land use types will have a value close to one.

Figures 11 and 12 show that meshblocks which contain a considerable amount of commercial and retail land tend to attract other land use types as well. Meshblocks in city centres have higher land-use diversity than those in the peripheries. Meshblocks that contain a significant amount of forestry and parks also scored lower because they are very homogenous. An anomaly identified in Figure 10 is that larger meshblocks show high levels of LUM, one of the drawbacks identified in the literature (Agampatian, 2014). In Figure 12, Featherston, Greytown, Carterton and Masterton had higher land-use mix in the centre of town with the outskirts being mostly homogenous.

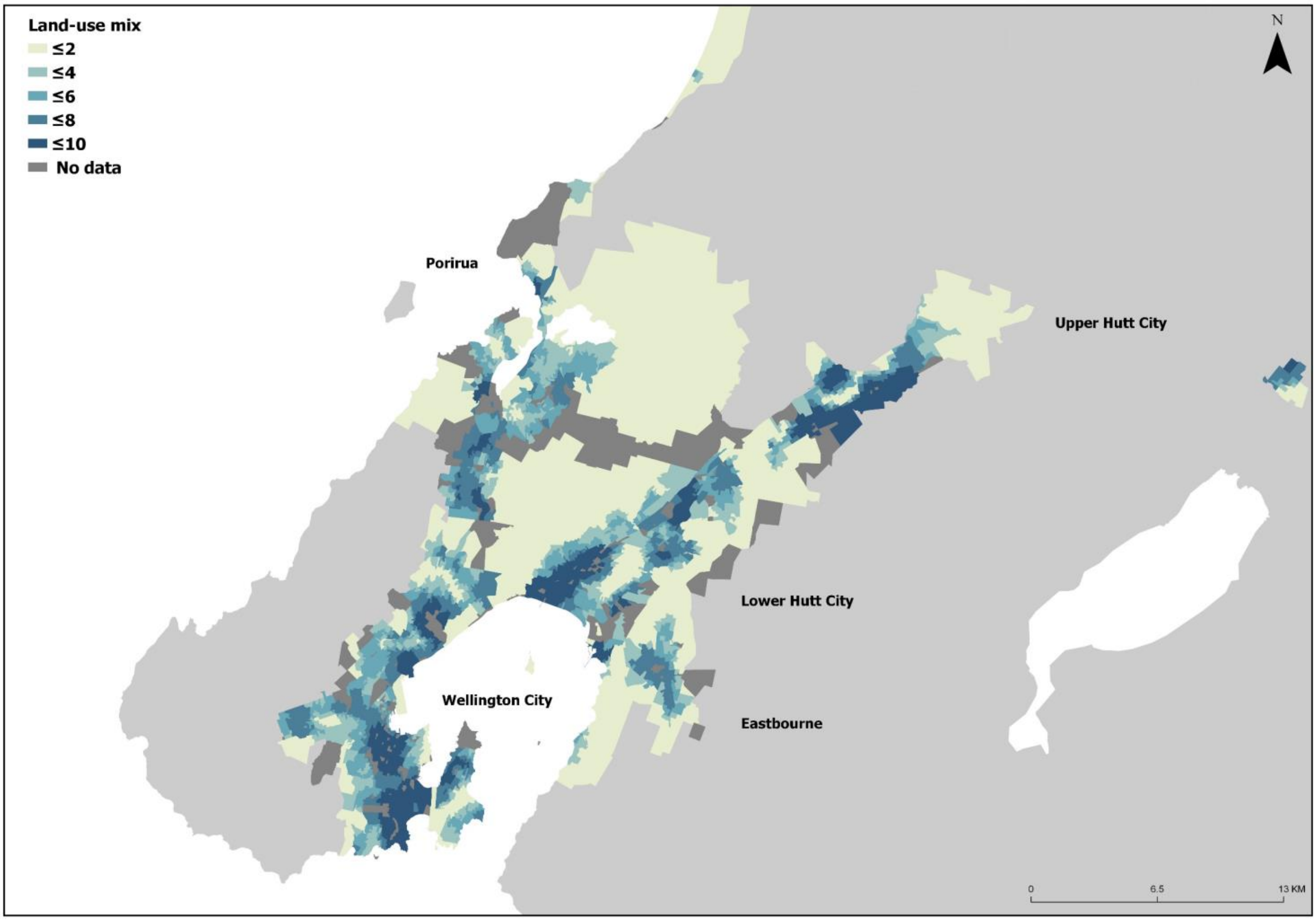


Figure 11. Land-use mix map of Wellington Region - Entropy index (Euclidean) (Map1)

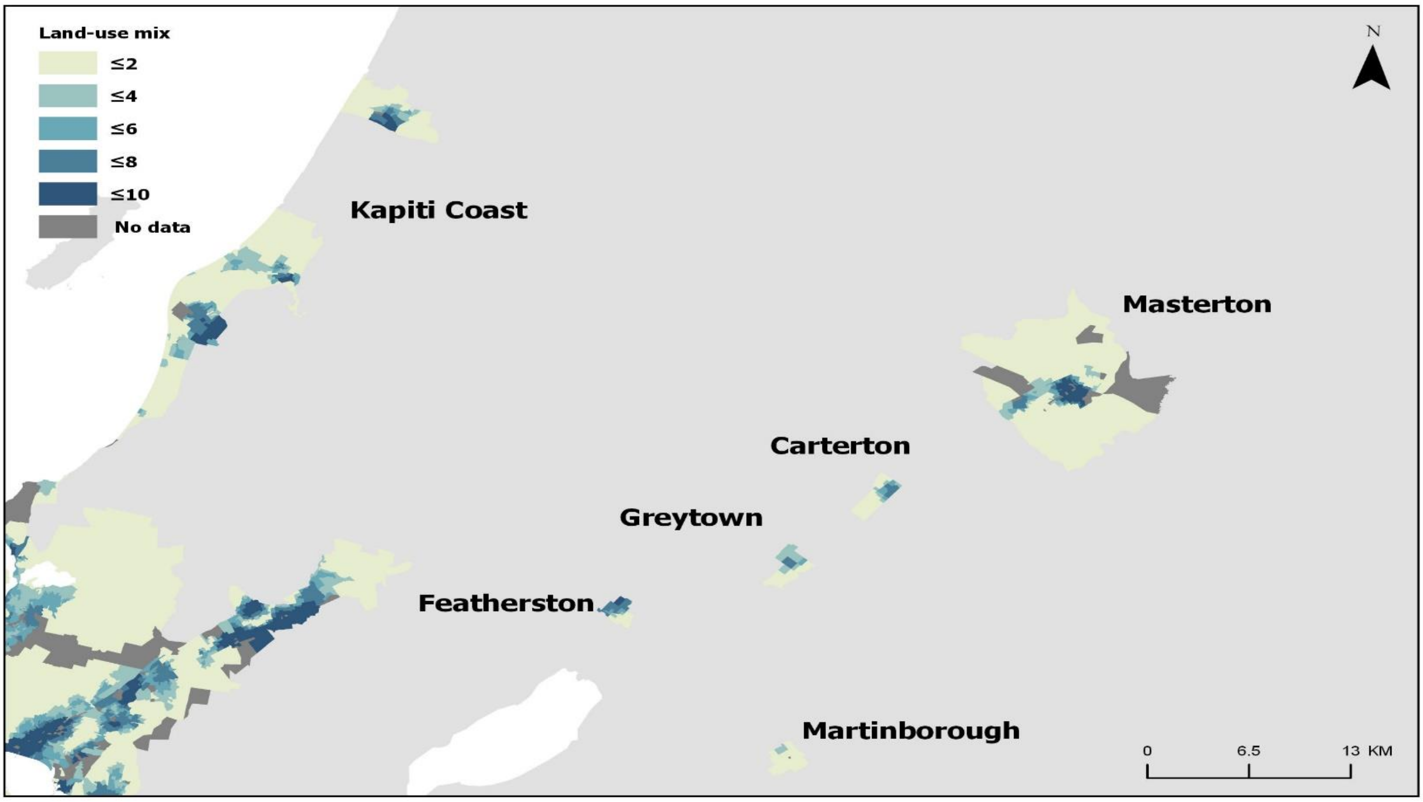


Figure 12. Land-use mix map of Wellington Region - Entropy index (Euclidean) (Map2)

Intersection Density

Intersection density refers to the amount of intersections within a given area. As intersection density increases, block size decreases and smaller blocks make neighbourhoods more walkable. According to Ewing and Cervero (2010), of all the connectivity measures available, intersection density has the largest effect on walking, use of public transport and driving. It can be measured by counting the number of real nodes in a given area. The higher the number of real nodes, the greater the number of intersections and presumably, higher connectivity. Intersection density was calculated using a road layer, obtained from Land Information New Zealand (LINZ). Intersections were calculated using the "*line to intersections*" tool in QGIS. The total number of intersections within each Euclidean buffer was calculated using the "*summarize within*" tool.

GIS Method Insert

The intensity of intersections in each meshblock area was calculated using the equation below:

$$\textbf{Intersection density} = \frac{\text{Number of intersections in a meshblock}}{\text{meshblock area (m}^2\text{)}}$$

Figures 13 and 14 show that meshblocks that are sparsely populated or located in the periphery demonstrate decreased intersection density. Meshblocks located in city centres show high intersection density. The highest intersection density was observed in the Wellington City centre, which also has the highest population density. Similarly, in the Wairarapa area the highest intersection densities are in the city centre. This is particularly evident in Masterton, where there are very low intersection density values (approx. decile 2). In the Kapiti Coast there appears to be more of an even distribution of intersections as there are multiple small towns in the area.

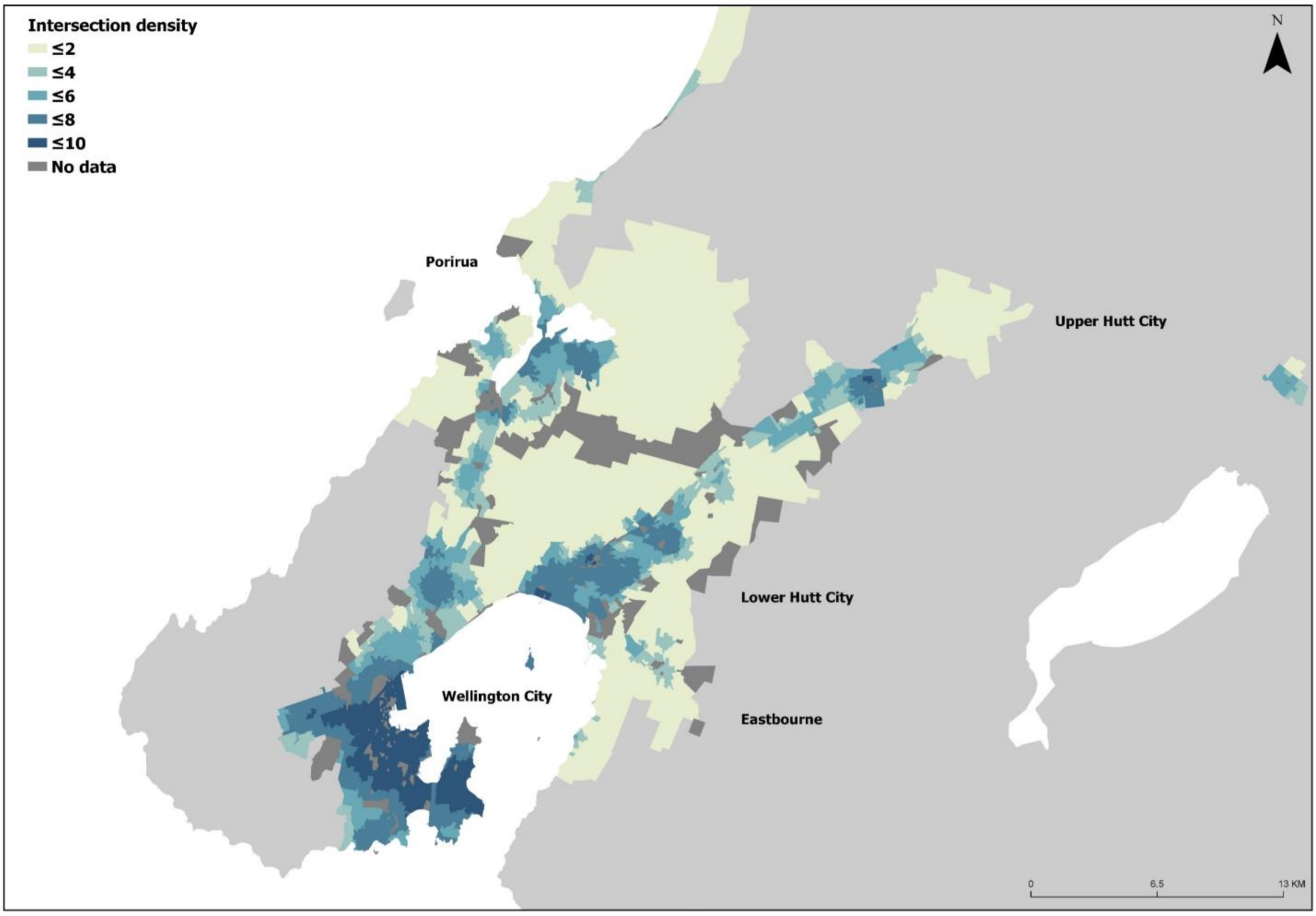


Figure 13. Intersections map of Wellington Region - Intersections per m2 (Euclidean) (Map1)

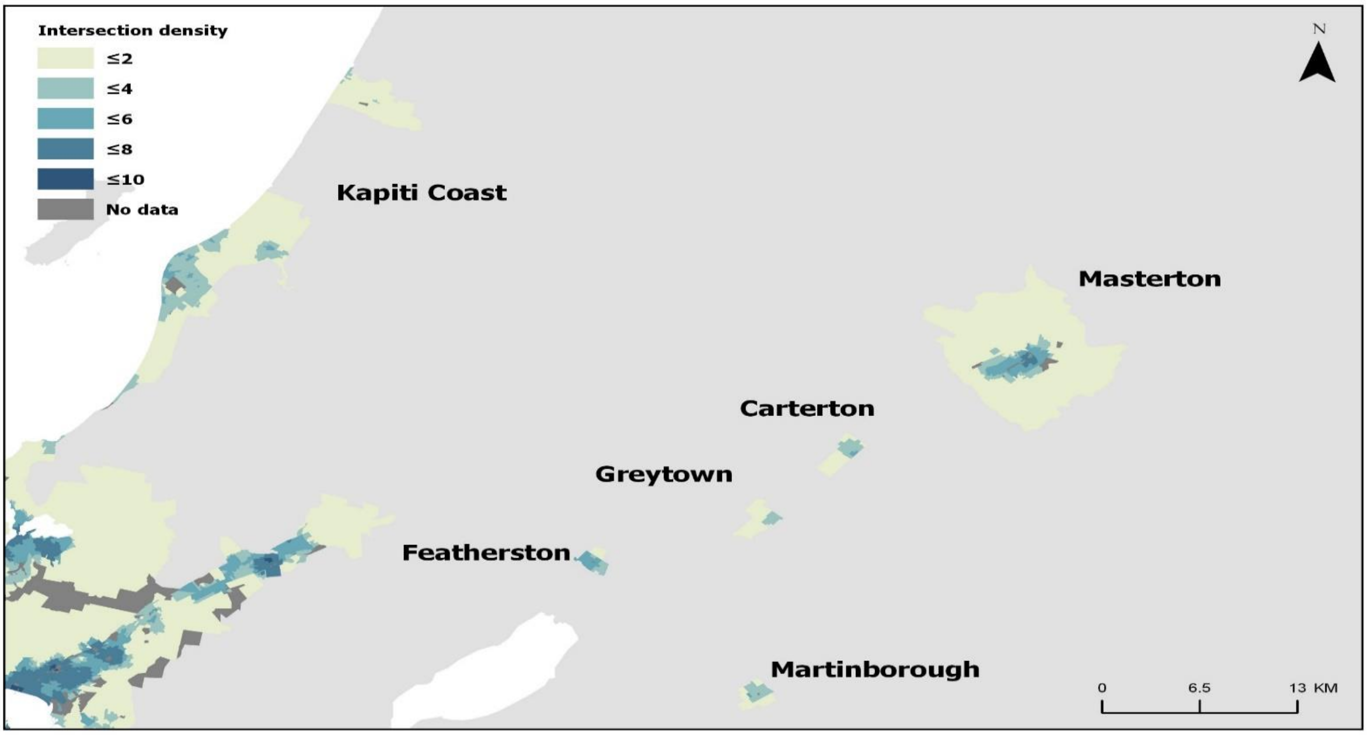
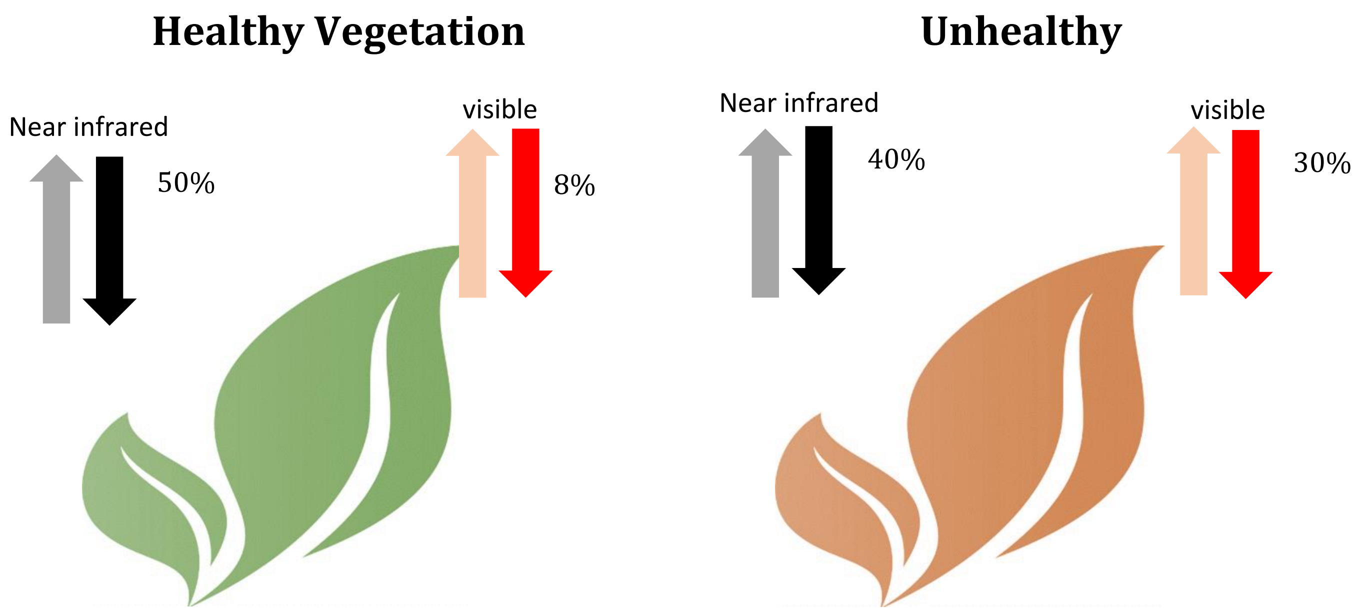


Figure 14. Intersections map of Wellington Region - Intersections per m2 (Euclidean) (Map2)

Mean Normalised Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) was used as a measure of exposure to green space. The NDVI determines the density of green on an area of land and can be calculated by observing the visible and near-infrared wavelengths reflected by plants (Rhew, Vander Stoep, Kearney, Smith, & Dunbar, 2011). As seen in Figure 15, healthy vegetation (left image) absorbs a large proportion of the visible light and reflects most of the near-infrared light (NIR). In comparison, unhealthy vegetation (right image) reflects more visible light and less NIR. The NDVI was calculated at the top of the atmosphere using satellite imagery derived from Landsat imagery archives (30 m resolution), so all atmospheric effects were normalised (the atmosphere-induced noise embedded in the satellite signal has mainly been removed). (Chander, Markham et al. 2009). This data was then used to calculate the mean NDVI value for each meshblock, and the resulting values aggregated for each data zone.



$$\frac{0.5-0.08}{0.5+0.08} = 0.72 \qquad \frac{0.4-0.3}{0.4+0.3} = 0.14$$

Figure 15. NDVI calculaation diagram

Figures 16 and 17 show that NDVI values are lower in built-up areas and higher in areas outside of the city centres. This pattern is particularly evident in Wellington City while Porirua City appears to have relatively even distribution of high NDVI values within the city centre and its periphery. In rural towns such as Masteton, Featherston, Caterton and Greytown, the mean NDVI values appear to mostly be above decile 4, indicating that the areas are not as built up.

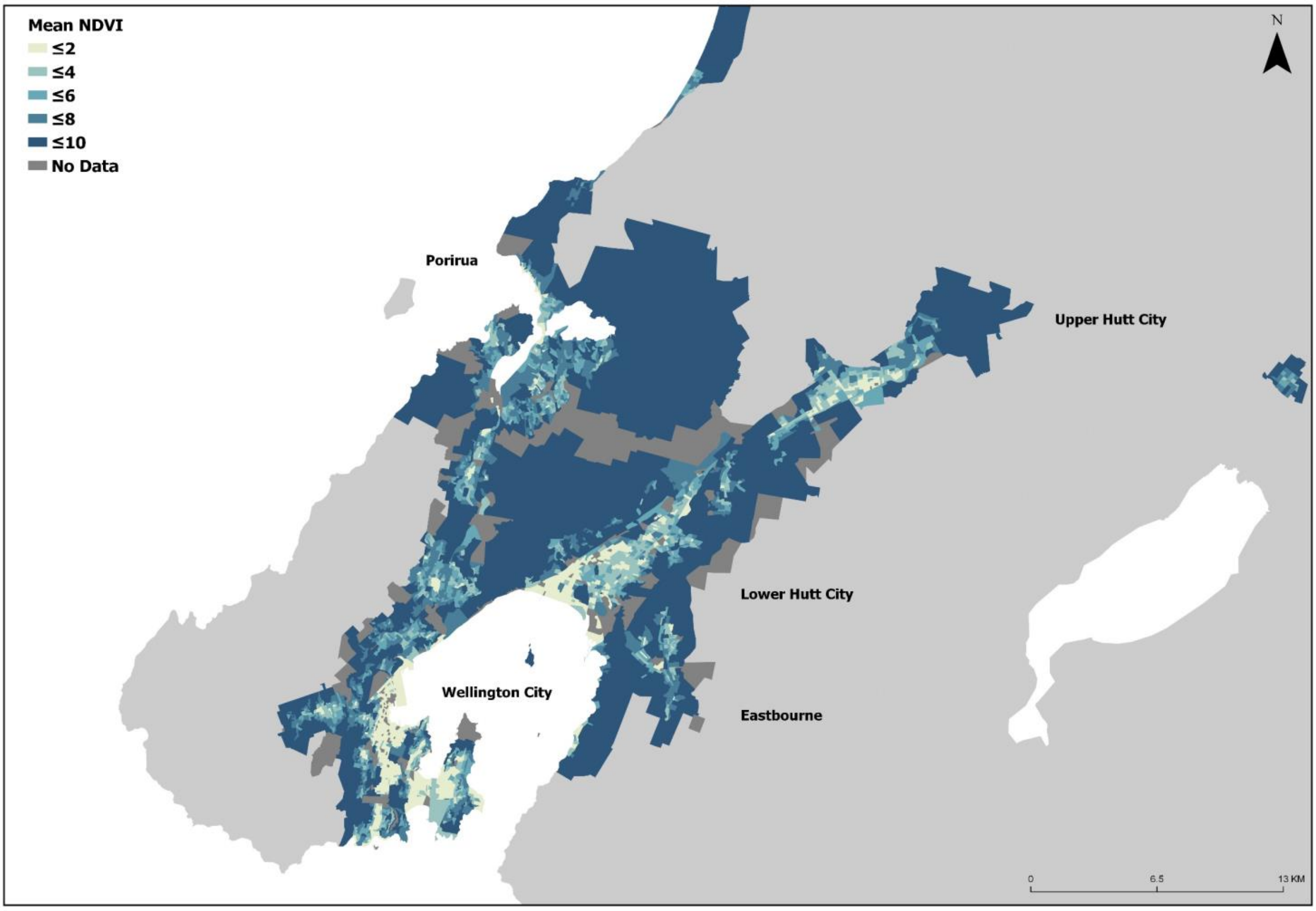


Figure 16. Mean NDVI map of Wellington Region (Euclidean) (Map1)

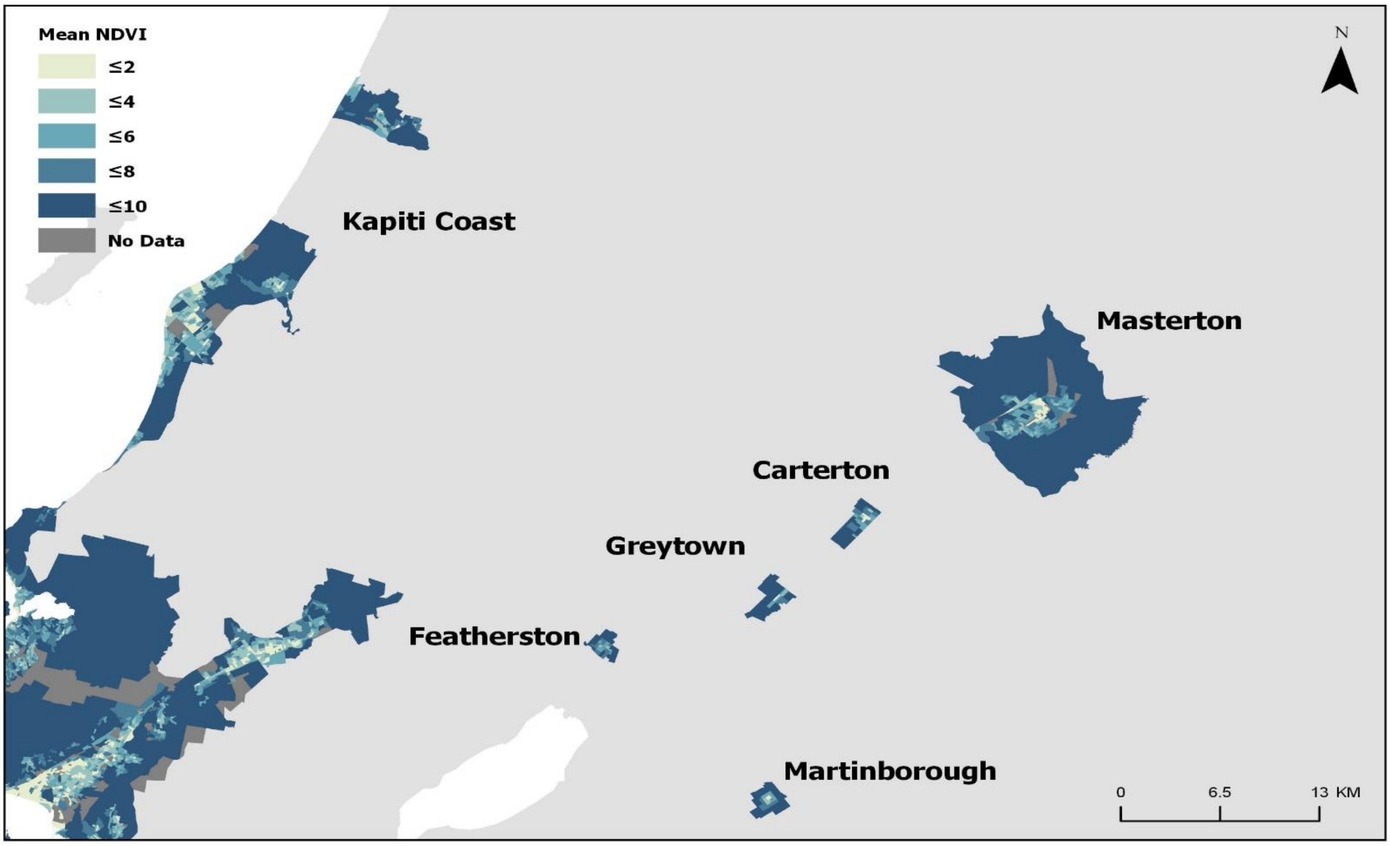


Figure 17. Mean NDVI map of Wellington Region (Euclidean) (Map2)

Average traffic volume

Low levels of traffic volume encourage pedestrians to walk in the street. High traffic volume suggests greater difficulty and less safety for pedestrians to crossroads. Average traffic volume was calculated using the National Road Centreline dataset from the New Zealand Transport Agency. This dataset is a combination of both public and private data and is supplied by Regional Council Authorities (RCA), or councils. The National Road Centreline was converted to a point shapefile, with each point containing an average traffic volume (the average daily traffic volume at a given location over a year (AADT)) for a specific road within the Wellington Region.

The average traffic volume in each meshblock area was calculated using the "*summarise within*" tool.

Traffic volume is higher in meshblocks located within proximity of city centres and decreases in meshblocks located in the outskirts of towns and cities (Figures 19 and 20). There is a very clear demarcation between Wellington City and Upper Hutt City, which shows the major highway. In the Wairarapa region, traffic volume is high in the centre of Masterton and the areas leading to Wellington City and Palmerston North.

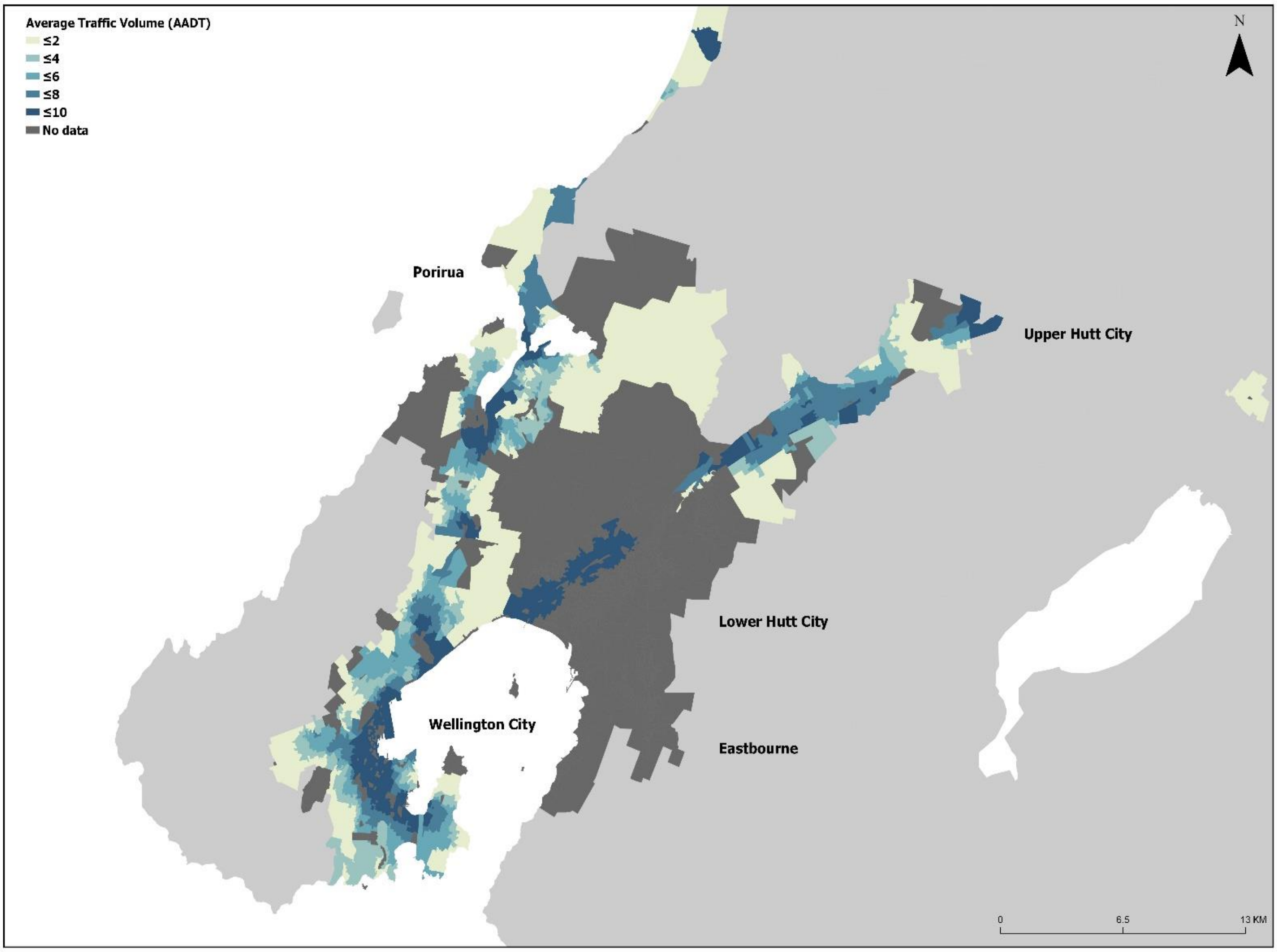


Figure 18. Average traffic volume map of Wellington Region (Euclidean) (Map1)

Figure 19. Average traffic volume map of Wellington Region (Euclidean) (Map2)

Walkability

The walkability index was calculated by summing the walkability scores of each measure after converting them to deciles. Each meshblock was given a rank according to the built environment features that promote or deter walkability. The standardisation to deciles was required as none of the measures were calculated in the same unit.

The deciles of each measure were simply added according to the equation shown below, in order to provide the final walkability score for each meshblock. Values close to one indicate low walkability, while values close to 10 indicate high walkability.

Walkability index = Intersection Density + Dwelling Density + Land-Use Mix + Normalized Difference Vegetation Index + Average Traffic Volume

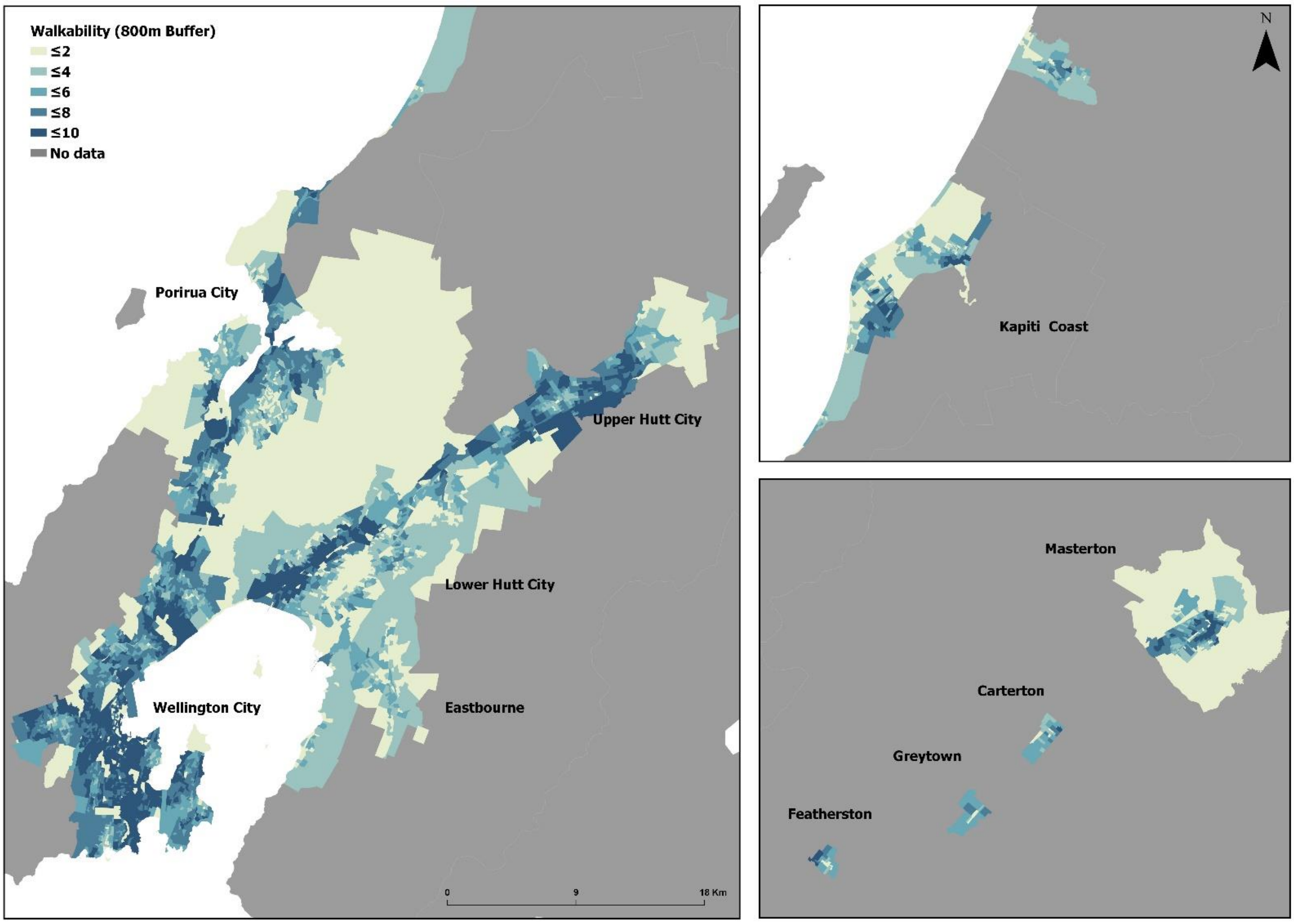


Figure 20. Walkability map of Wellington Region (Euclidean)

Figure 20 shows that the most walkable areas of the Wellington Region are Wellington City and Upper Hutt City. This is further supported by the hot spot analysis shown in Figure 14.

Hot spot analysis

A spatial cluster analysis was completed to determine the distance band at which maximum special autocorrelation occurs (3321.2 meters). Results of the Moran's I test in Figure 21, and Table 2 indicate that given the z-score of 352.8, there is a less than 1% likelihood that the clustered pattern of walkability in the Wellington Region is the result of random chance (p= 0.000000 at CI=95%).

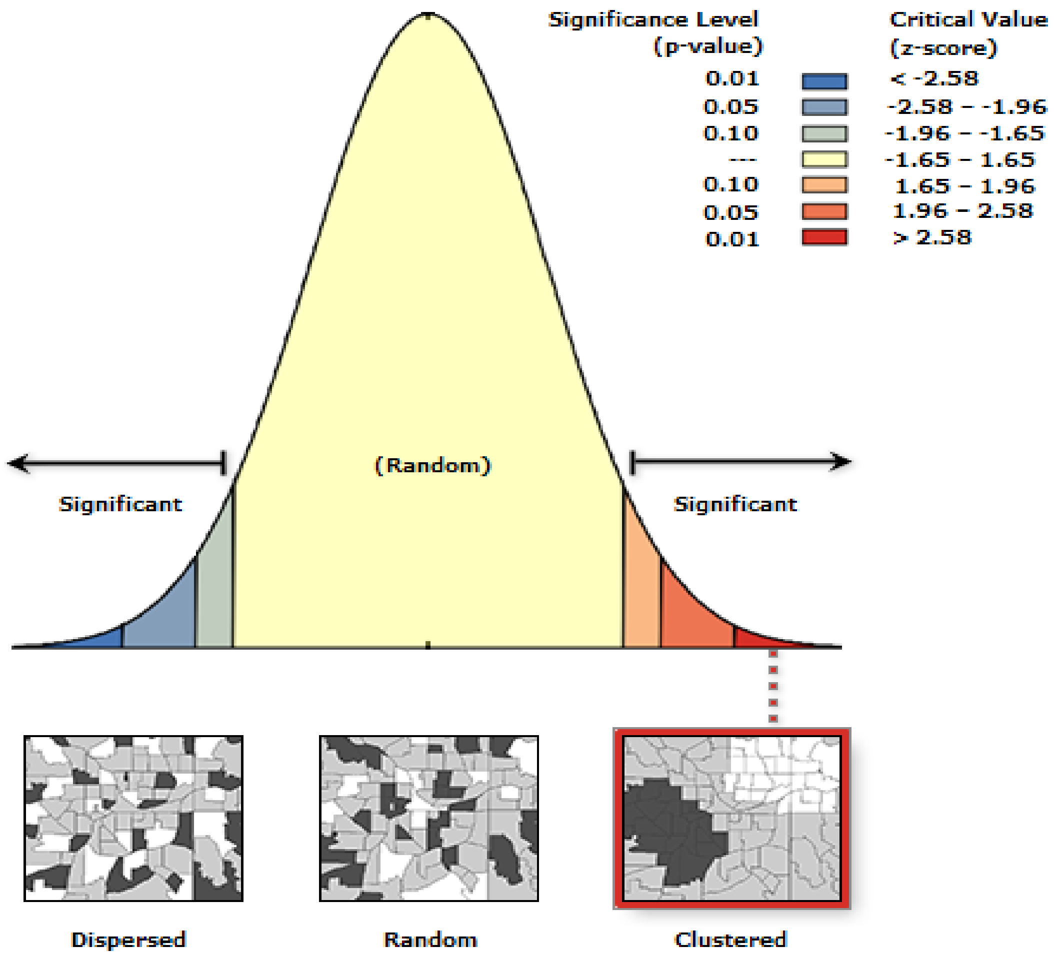


Figure 21. Spatial autocorrelation – Walkability (Euclidean)

Table 2. Global Moran's I summary - Walkability (Euclidean)

Global Moran's I Summary	
Distance threshold	3341.2m
Moran's Index	0.541036
Expected Index	-0.000205
Variance	0.000002
Z-score	352.797240
P-value	0.000000
Distance method	Euclidean
Conceptualization	Inverse distance

To take the analysis of the Wellington Region further, the next process involved using spatial statistics to perform a Hot Spot Analysis (Getis-Ord Gi*) of walkability. The results from this analysis produced z-scores and p-values which show where meshblocks with either high or low values cluster spatially. The analysis tool looks at each meshblock within the context of other neighbouring meshblocks. While a meshblock with a high value may be of particular interest, it may not be a statistically significant hot spot. In order for a meshblock to be statistically significant, it must have a high value and be surrounded by other high-value meshblocks.

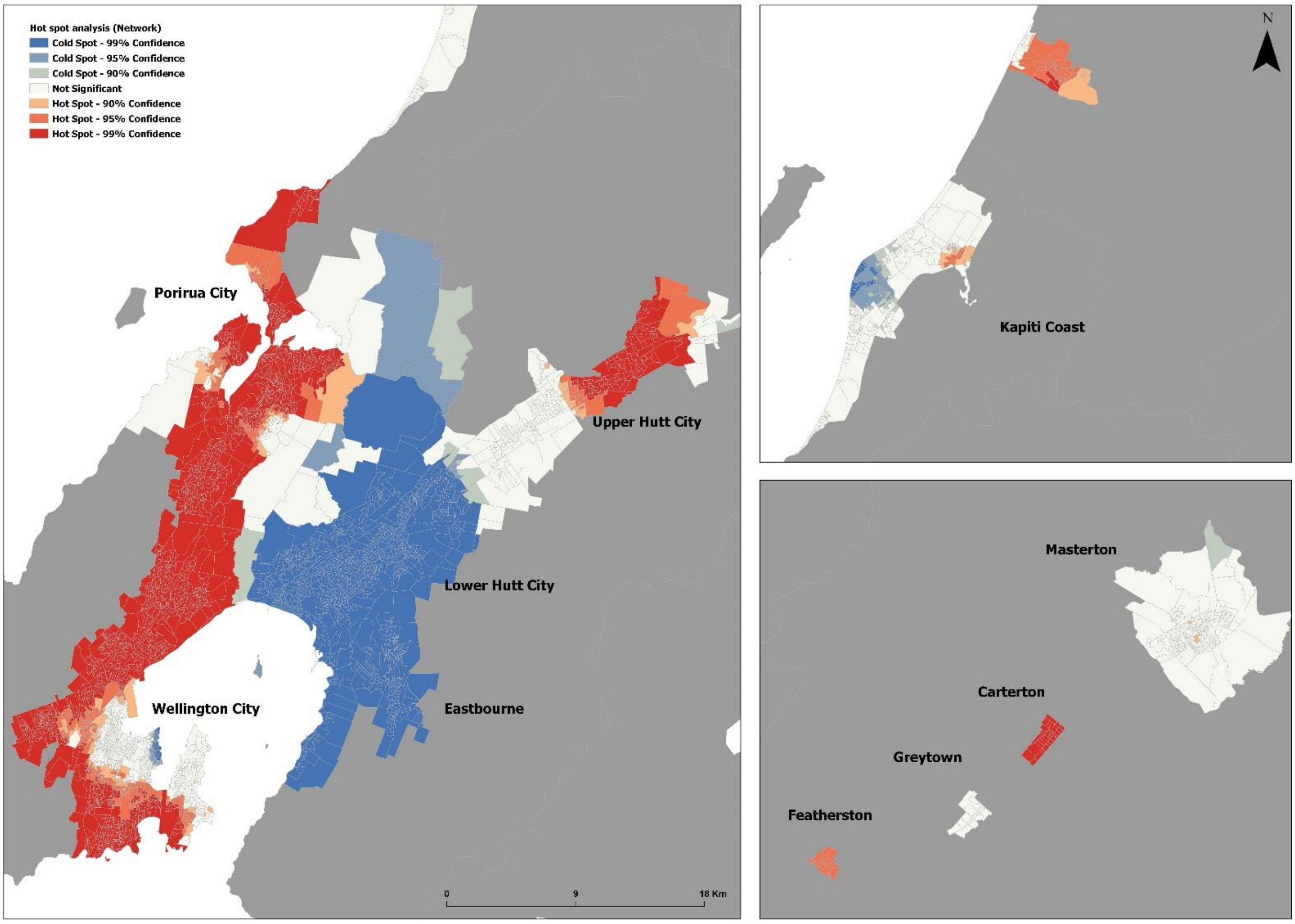


Figure 22. Hot spot map of Wellington Region (Euclidean)

As mentioned previously in Figure 20 the most walkable areas appear to be Wellington City and Upper Hutt City. Figure 22 supports this and shows that Wellington City and Upper Hutt City are statistically significant hot spot clusters (red shading) of meshblocks with high walkability. Significant cold spot meshblock clusters (blue shading), with low walkability, are located Lower Hutt City, Porirua City, Otaki and the outskirts of Masterton. As these areas are mostly rural, there is evidence to support the development of a separate walkability index for rural areas. The majority of the measures used in this study being indicators of urbanity.

4.5 Developing a network-based walkability index

In this section, the previous measures (dwelling density, land-use mix, intersection density, NDVI and average traffic volume) were recalculated using an 800m network buffer

Dwelling density

Similar to the Euclidean buffer analysis in Figures 9 and 10, the map shown in Figure 23 indicates a relatively even spread of dwelling density throughout the Wellington Region, with the densest meshblocks located just outside of the city centres, where the residential areas are largely located. In comparison to Figures 9 and 10, there appears to be no clustering of areas of high dwelling density due to the network buffer method only accounting for areas that individuals can access by road. For instance, the Euclidean buffer method (Figures 9 and 10) shows high dwelling density in areas known to be forest and open space. In Masterton, Carterton, Featherstone, Kapiti and Porirua City, there appears to be an even spread of dwelling density with no particular area being high or low in density. In comparison, Greytown has a high dwelling density located centrally and low dwelling density in the outskirts.

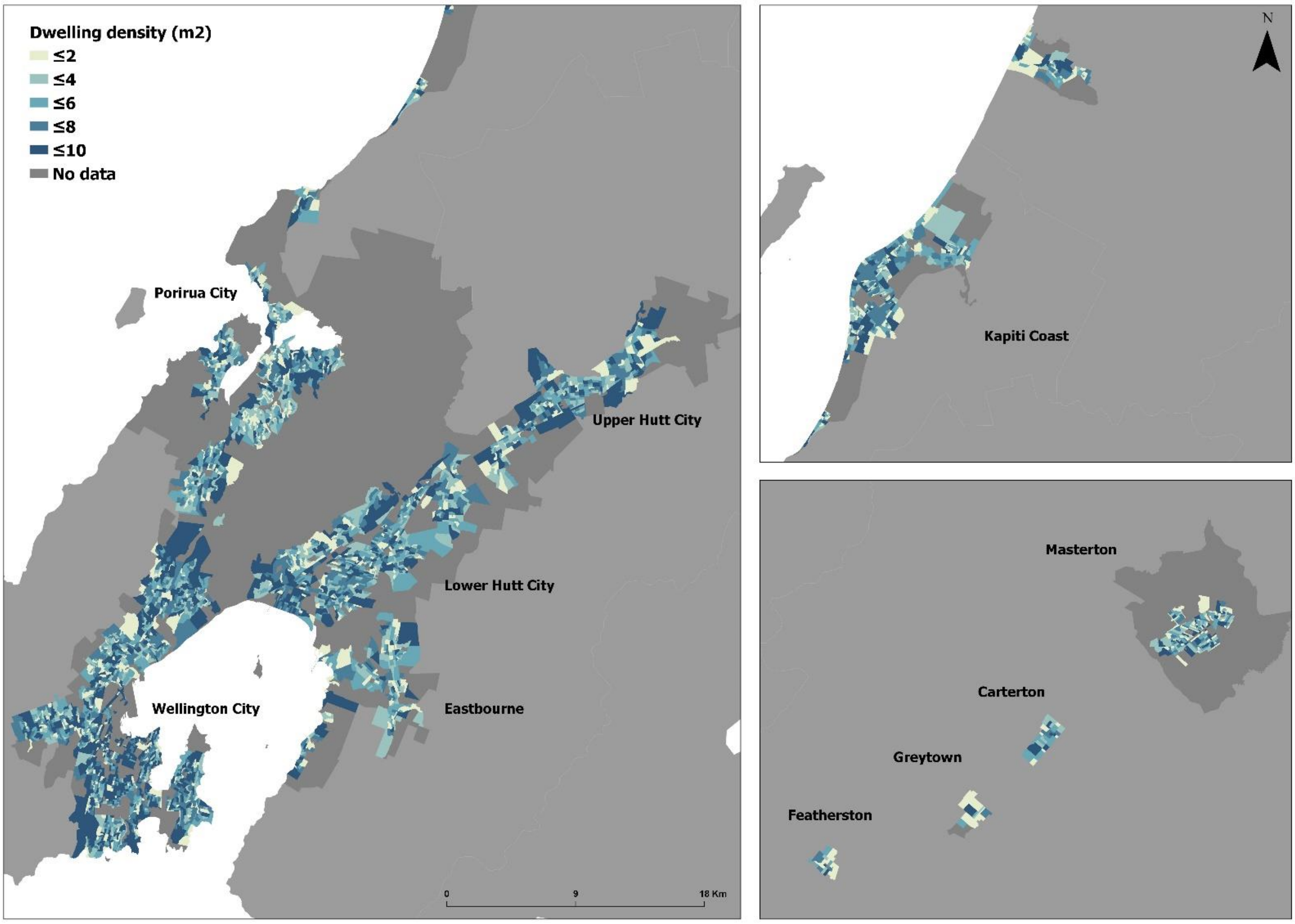


Figure 23. Dwelling density map of Wellington Region – Dwellings per m2 (Network)

Land-use mix

In comparison to the Euclidean buffer derived land-use mix in Figures 11 and 12, the network buffer land-use mix shows a greater mix of diversity and homogeneity. The Euclidean buffer method showed that meshblocks located in the city centres had a higher land use diversity score than those in the peripheries. In contrast, Figure 24, which used the 800-network buffer, shows no particular areas with a high concentration of diversity. However similar to Figures 11 and 12, there are numerous areas of homogeneity, which are mostly open space, forestry and parks.

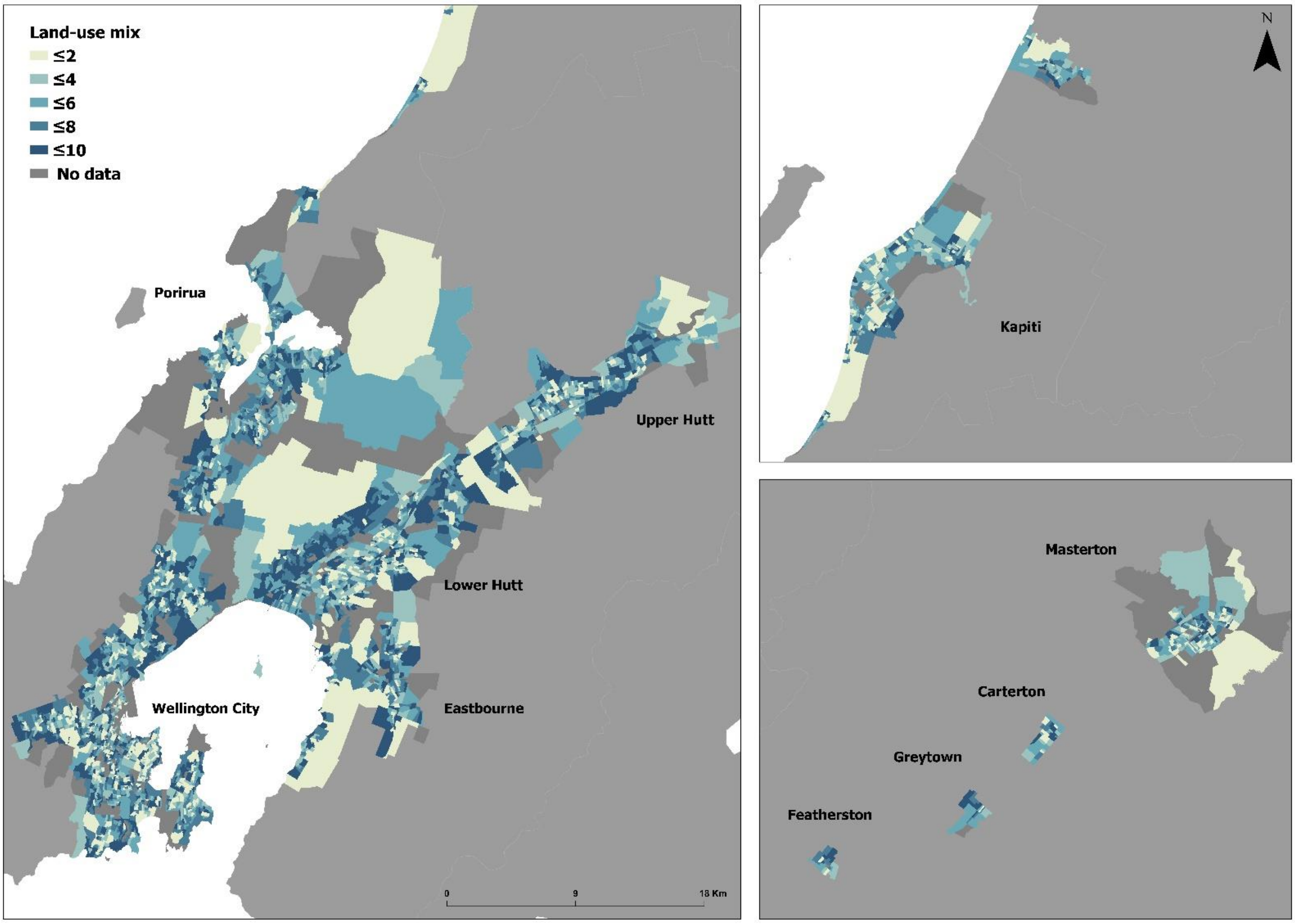


Figure 24. Land-use mix map of Wellington Region - Entropy index (Network)

Intersection density

Results from the network buffer in Figure 25 show a relatively similar pattern to that of the Euclidean buffer in Figures 13 and 14. Meshblocks that are sparsely populated demonstrate decreased intersection density. While meshblocks located in city centres show high intersection density and low intersection density in areas located in the periphery.

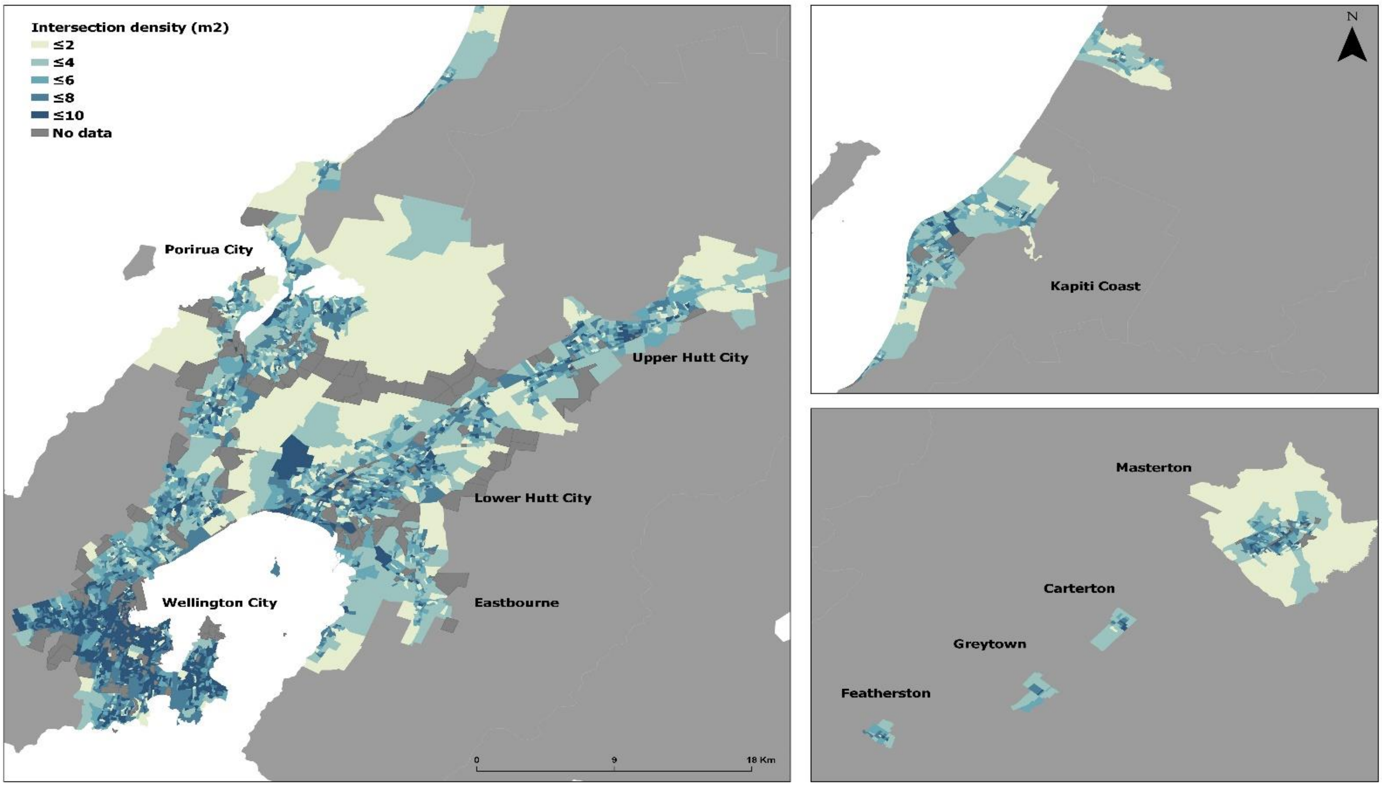


Figure 25. Intersections map of Wellington Region - Intersections per m² (Network)

NDVI

Figure 26, using the Network buffer method has a similar pattern to the Euclidean buffer method used in Figures 16 and 17, which shows that NDVI values are lower in built-up areas and higher in areas outside of the city centres.

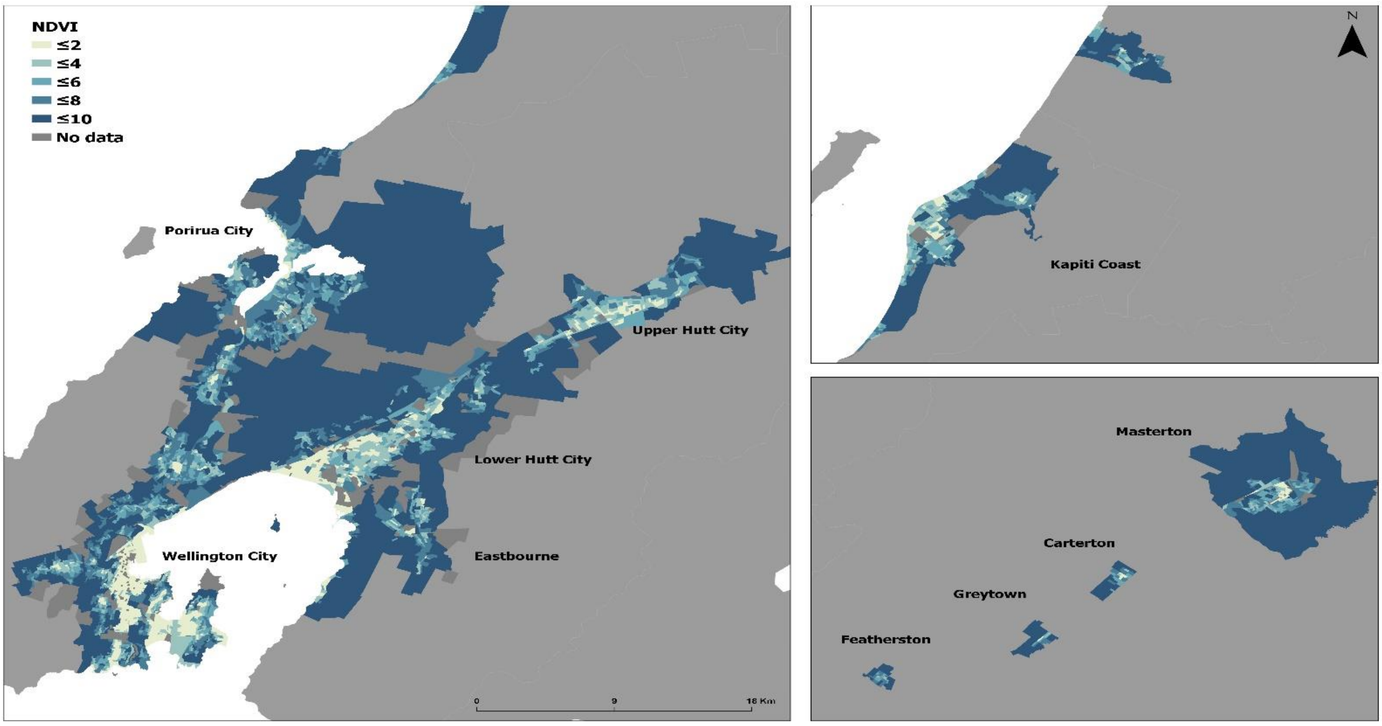


Figure 26. Mean NDVI map of Wellington Region (Network)

Average traffic volume

The strong and clear pattern observed in the previous map (Figures 18 and 19) is not as evident in the network-based average traffic volume measure below (Figure 27).

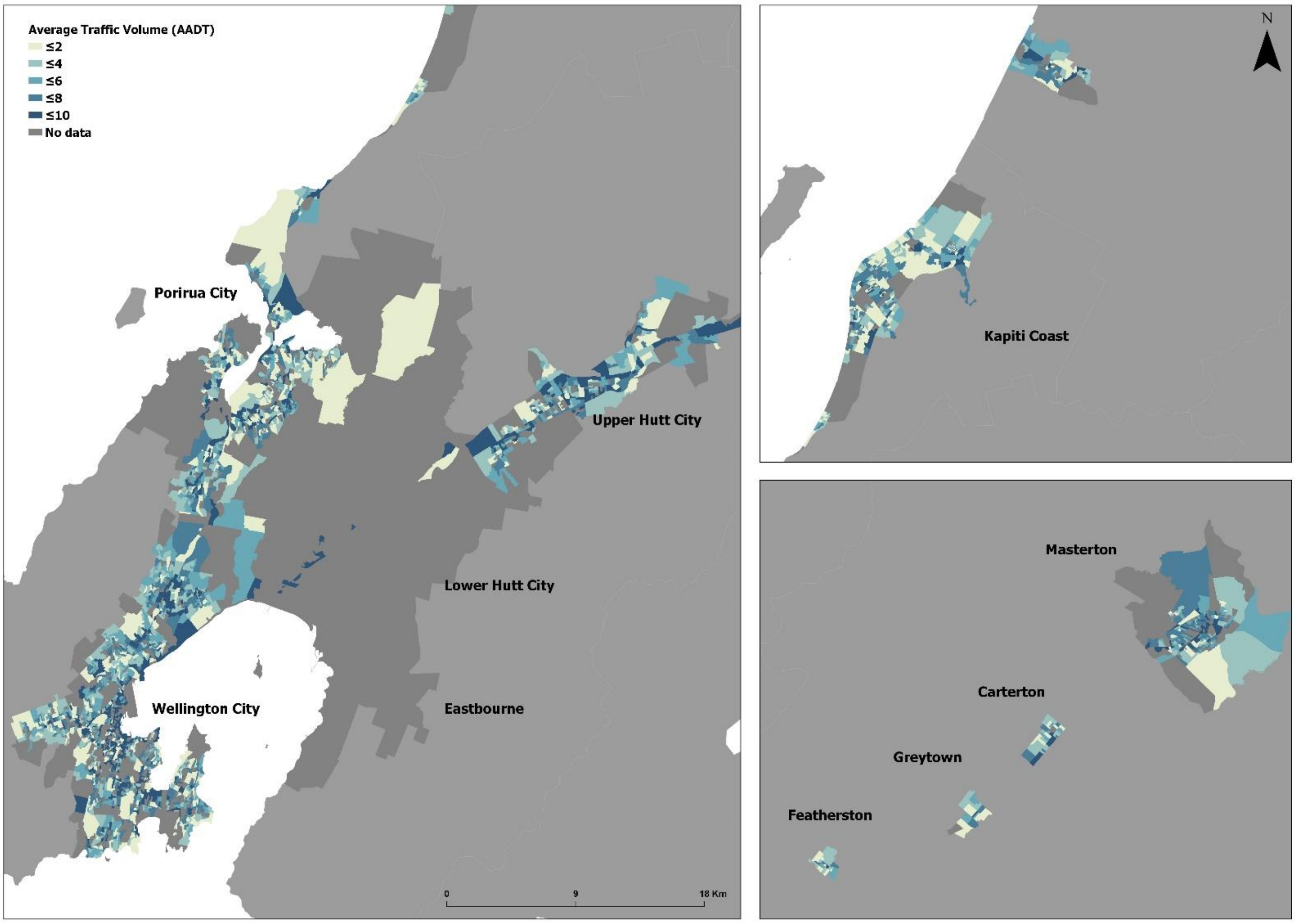


Figure 27. Average traffic volume map of Wellington Region (Network).

Walkability

The results shown in Figure 28 from the network-based analysis, indicate that Wellington City and Upper Hutt City still contain statistically significant hot spot clusters of meshblocks with high walkability. Significant cold spot meshblock clusters (blue shading) with low walkability are located in Lower Hutt City, Porirua City, and Otaki. The most noteworthy difference between the Euclidean and network buffer findings is the non-significance of walkability results in the Wellington City centre and lack of statistically significant cold spot (low walkability) meshblock cluster in the outskirts of the Masterton region.

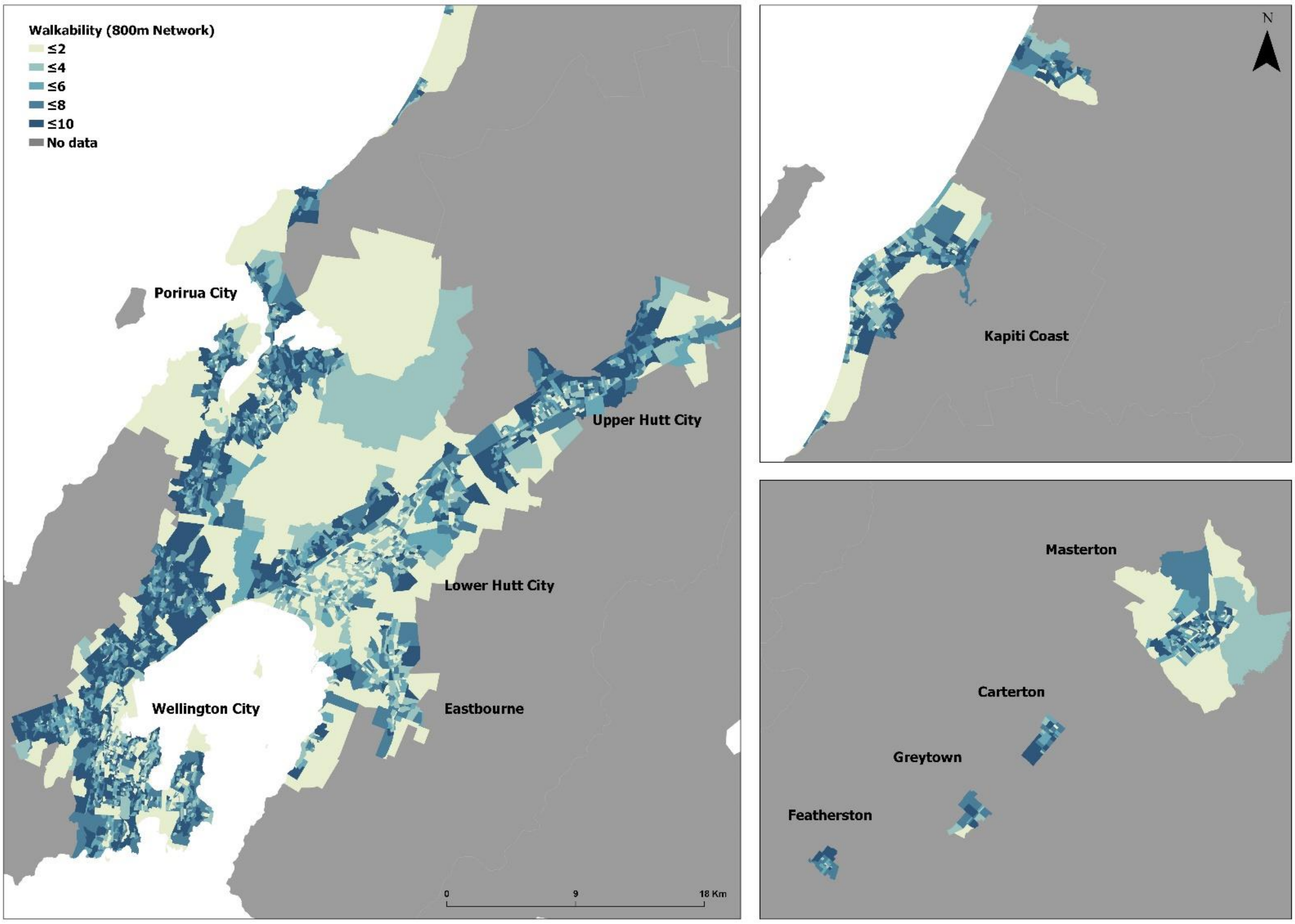


Figure 28. Walkability map of Wellington Region (Network)

Hot spot analysis

Results from the network-based analysis indicated that the distance band at which maximum special autocorrelation occurs is 3341.2 meters. Results of the Moran's I test in Figure 29, and Table 3 indicate that given the z-score of 95.1, there is a less than 1% likelihood that the clustered pattern of walkability in the Wellington Region is the result of random chance (p= 0.000000 at CI=95%).

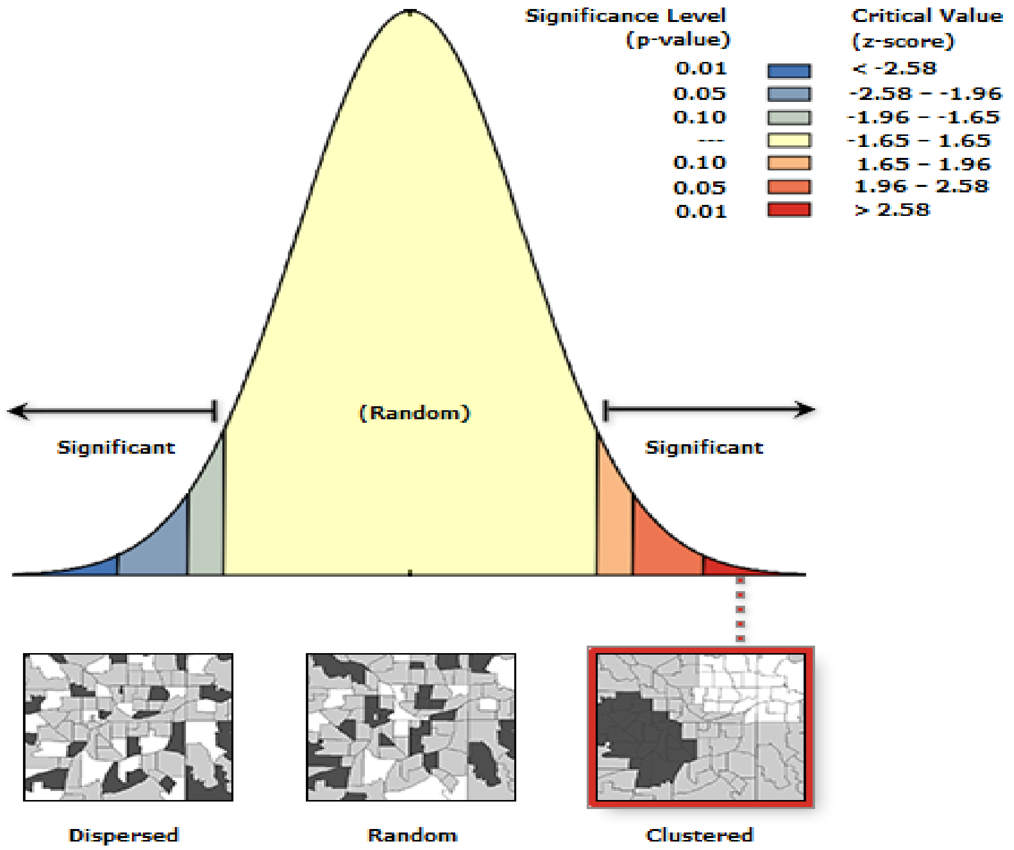


Figure 29. Spatial autocorrelation report – Walkability (Network)

Table 3. Global Moran's I summary - walkability (Network)

Global Moran's I Summary	
Distance threshold	3341.1 m
Moran's Index	0.145694
Expected Index	-0.000205
Variance	0.000002
Z-score	95.101487
P-value	0.000000
Distance method	Euclidean
Conceptualisation	Inverse distance

The results from the hot spot analysis (Getis-Ord Gi*) analysis of the network-based walkability index are presented below in Figure 30.

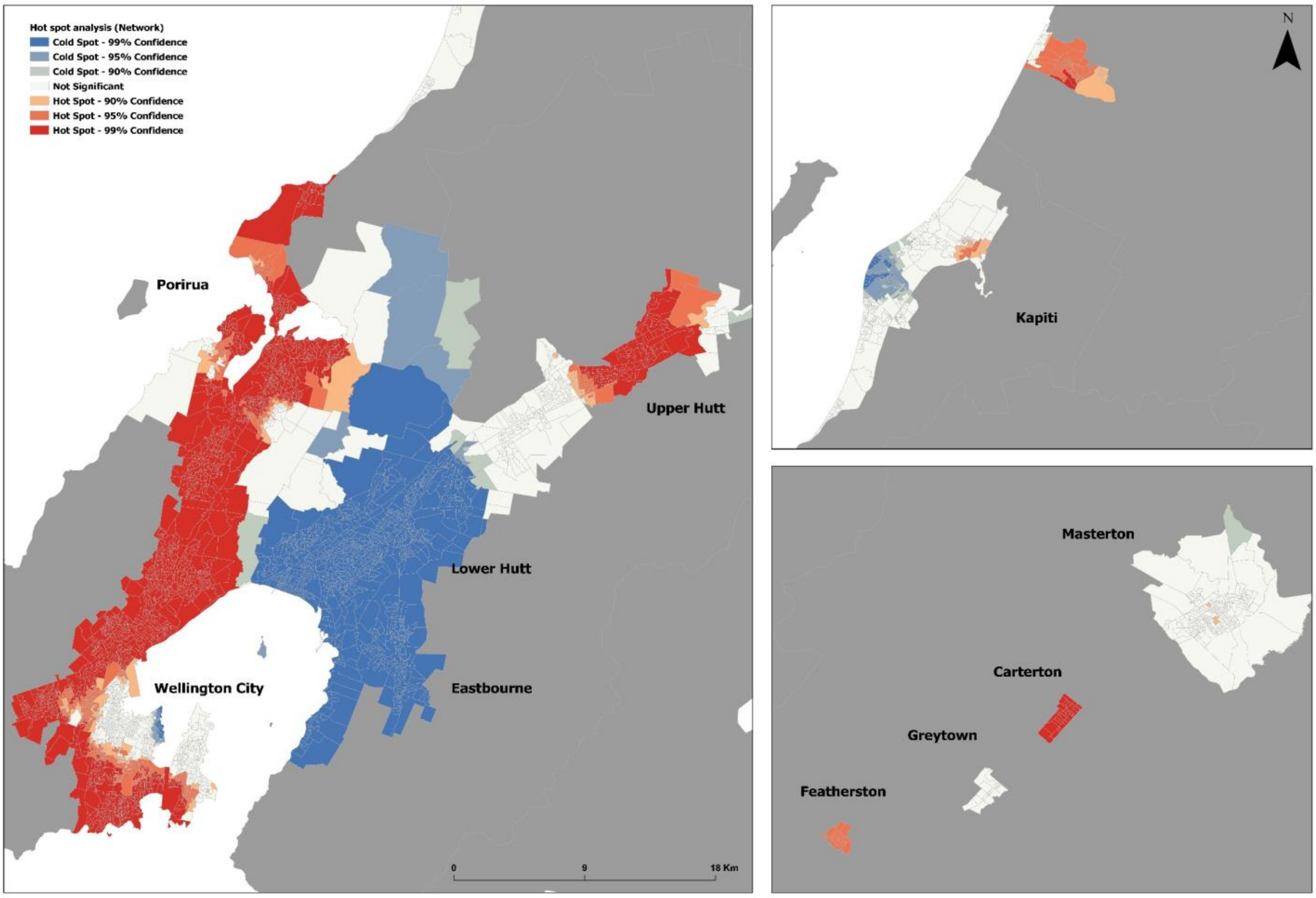


Figure 30. Hot spot map of Wellington Region (Network)

Similar to Figure 22, the finding above (Figure 30) show that Wellington City and Upper Hutt City are statistically significant hot spot clusters (red shading) of meshblocks with high walkability. Significant cold spot meshblock clusters (blue shading), with low walkability, are located in Lower Hutt City and some areas of the Kapiti Coast. In comparison to the previous analysis in Figure 22, the network-based findings indicate that Featherston, Carterton and Otaki have statistically significant hot spot clusters.

Chapter 5: Validating the walkability index

5.1 Overview – Active travel data

An initial exploration of the dataset in Figure 31 revealed that within the active travel variable, approximately 48.9% of the dataset consisted of zeros.

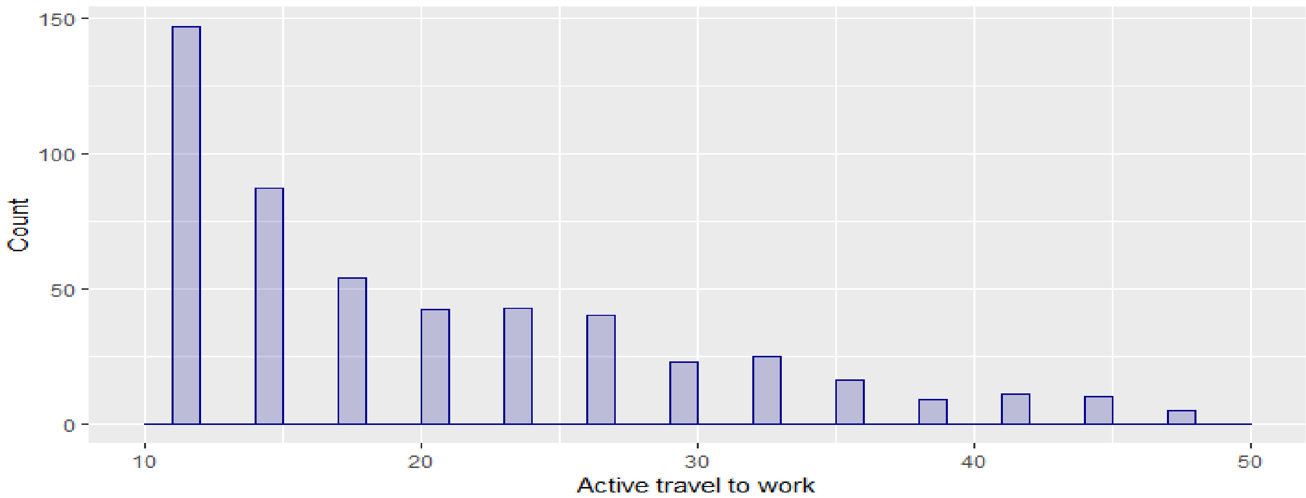


Figure 31. Histogram of active travel to work on Census day

Additionally, Table 4 suggests that a walkability decile is a good candidate for predicting the number of participates who walked or cycled to work, because the mean value of the outcome appears to vary by decile. The standard deviations within each level of walkability are higher than the means within each level. These are the conditional means and standard deviations, and these differences along with the dependent variable being a count suggest that over-dispersion is present, suggesting that a typical linear model is not appropriate for this analysis. A more appropriate model would be a generalised linear model (GLM), which can handle the distribution of the count variables. However, due to the various ways that count variables can be distributed, there are multiple forms of the GLM for count data.

Table 4. Number of active travellers by walkability decile (Euclidean example)

Walkability (Buffer)	Mean	SD
Low Walkability 1	n/a	n/a
2	1.73	2.84
3	1.84	3.13
4	2.15	3.37
5	2.98	4.24
6	3.77	7.85
7	4.29	7.98
8	7.57	16.07
9	8.71	14.69
High Walkability 10	15.38	23.27

5.2 Comparing regression models

Before the development of regression models for count data, count variables were usually handled in two main ways. Firstly, researchers would use typical linear models under the assumption that they were robust enough to handle any assumption violations (Beaujean & Morgan, 2016). Secondly, count variables were transformed to make them fit traditional models. Overall, these two approaches were significantly problematic. Research has shown that traditional models tend to produce inflated standard errors and makes continuous predictions even though count outcomes are discrete, therefore violating the assumption of heteroscedastic (the same variance) in the traditional models (Beaujean & Morgan, 2016). Which is where generalised linear models come into play as these models can handle the distribution of count variables. The following section explores various models in order to determine the most appropriate method to use for this research.

The two main methods used in this thesis to compare competing models are Akaike's Information Criterion (AIC) and Schwartz's Bayesian Information Criterion (BIC). These information criterion based fit indices are useful when presented with numerous possible models. The AIC is used to estimate the relative quality of a statistical model's goodness-of-fit to the data. According to Anderson and Burnham (2002), the general method used to pick the best model is to select the smallest AIC value. However, it is important to note that AIC values should not be interpreted alone as they are highly influenced by sample size. The BIC was also used and similar to the AIC method, the model with the smallest value was selected.

Poisson regression was performed, followed by a negative binomial (NB) regression. A comparison between the two regression models shows that there appears to be enough overdispersion in the Active travel variable that the Poisson model was not able to capture the variance as well as the NB model. A comparison of the negative binomial, Hurdle and zero-inflated negative binomial (ZINB) models show that while the Hurdle model is better than NB model, it is not an improvement on the ZINB models which has slightly lower AIC and BIC values. Therefore, the ZINB models were used to determine associations between the indices of the built environment and active transport modes. The difference between the Hurdle and ZINB models is that the Hurdle model assumes that there is only one process by which a zero can be obtained, while ZINB models assume that there are two. For instance, in a Hurdle model, there are two types of outcomes, those who never experience the outcome and those who always experience the outcome at least once. While in ZINB models there are those who experience the outcome as well as those who can but do not always experience the outcome (Zuur & Ieno, 2016).

Table 5. Comparison of the regression models for the active travel data by AIC and BIC

Model	AIC	BIC
Poisson	30421.92	30589.21
NB	17398.73	17572.45
Hurdle	16391.07	16732.07
Zero-inflated	16382.50	16723.50

5.3 ZINB regression model (2013 New Zealand Census)

The following section explores the relationship between walkability and active travel by presenting results from the ZINB models for the Euclidean (Section 5.4) and network-based buffers (Section 5.5).

Zero-inflated negative binomial regression models are not conventional in health and environmental research; however; they are highly beneficial as they account for excess zeros and over-dispersion (Beaujean & Morgan, 2016). The ZINB regression model generates two separate models to distinguish behaviours of individuals, who did or did not walk or cycle to work. The first section of the model contains a NB model that predicts how frequently active travel occurred. The second section is a logit model, which predicts the non-occurrence of active travel (Beaujean & Morgan, 2016). The excess zeros in the active travel variable have two potential meanings; firstly, they can represent participants that generally walk or cycle to walk but did not on Census day. Secondly, they can also represent participants who never walk or cycle to work.

Table 6 presents an overview of the models applied, and the potential confounder variables included to determine associations between the Euclidean walkability, network walkability and walking and cycling to work. For each index, three models were completed.

Table 6. Models applied to test for associations between outcome and exposure variables using ZINB

	Model 1	**Model 2**	**Model 3**
Outcome Variable	**Exposure variables**	**Exposure variables**	**Exposure variables**
Walking and cycling to work	▪ Buffer walkability[1] index ▪ Network walkability index[1]	▪ Buffer walkability[1] index ▪ Network walkability index[1]	▪ Buffer walkability[1] index ▪ Network walkability index[1]
		The proportion of working age groups: -15-29 -30-44 -45-54 -55-64	**The proportion of working age groups:** -15-29 -30-44 -45-54 -55-64
		Proportion of ethnic groups: - Māori - Pacific - Asian - European/Other	**Proportion of ethnic groups:** - Māori - Pacific - Asian - European/Other
		The proportion of each sex ▪ Females ▪ Males	**The proportion of each sex** ▪ Females ▪ Males
			The 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 (1-10)

[1]Each walkability index was tested for associations separately due to being highly correlated

5.4 Results - Euclidean buffer

Model One

(Zero-inflated results). The baseline odds of never walking or cycling to work is 1.6 (Table 7). The odds are decreased by one unit increase in walkability by 0.8 (Table 7) (p <0.001). Meaning that as active travel decreases, walkability decreases.

(Count results). The baseline odds for the active travel variable is 1.97 (Table 7) among individuals who actively travelled to work on Census day. A unit increase in walkability increases the odds of actively travelling to work by 1.24 (Table 7) (p <0.001).

Table 7. Euclidean model one – Unadjusted

	Count model		Zero-inflated model	
Variable	**Estimate**	**Exponetiated coefficients**	**Estimates**	**Exponetiated coefficients**
Intercept	**0.68**	1.97	**0.47**	1.60
Walkability index				
Buffer800m	**0.22**	1.24	**-0.13**	0.88

Key: Values highlighted in bold indicate statistically significant associations

Model Two

Even after controlling for sex, age and ethnicity, the association between walkability and active travel to work are still statistically significant for both the count and zero-inflated models (p <0.001). A unit increase in walkability increases the odds of actively travelling to work by 0.95 (Table 8) (p <0.001). (*See table 15 in the appendix for all results*)

Table 8.Euclidean model two – Adjusted for demographics

	Count model		Zero-inflated model	
Variable	**Estimate**	**Exponetiated coefficients**	**Estimates**	**Exponetiated coefficients**
Intercept	-0.05	0.95	1.15	3.16
Walkability index				
Buffer800m	**0.10**	1.10	**-0.11**	0.90
Sex				
Age group				
15-29	**3.60**	36.75	**-5.65**	0.00
30-44	**2.47**	11.87	**-4.33**	0.01
45-54	0.27	1.30	**-5.17**	0.01
Ethnicity				
Māori	**-1.69**	0.18	1.29	3.14
Pacific peoples	**-2.16**	0.12	0.76	2.14

Key: Values highlighted in bold indicate statistically significant associations

Model Three

Even after accounting for demographics and socioeconomic factors, the association between walkability and active travel to work was still statistically significant for both the count and zero-inflated models (p <0.001).

(Zero-inflated results). The baseline odds of never walking or cycling to work is 4.22 (Table 9). The odds are decreased by one unit increase in walkability by 0.89 (Table 9) (p <0.001), this means that as active travel decreases, walkability decreases.

(Count results). The baseline odds for the active travel variable is 0.57 (Table 9) among individuals who actively travelled to work on Census day. A unit increase in walkability increases the odds of actively travelling to work by 1.09 (p<0.001). (*See table 16 in the appendix for all results*).

Table 9. Euclidean model three - Adjusted for socioeconomic and deprivation

	Count model		Zero-inflated model	
Variable	**Estimate**	**Exponetiated coefficients**	**Estimates**	**Exponetiated coefficients**
Intercept	-0.56	0.57	1.44	4.22
Walkability index				
Buffer800m	**0.08**	1.09	**-0.11**	0.89
Sex				
Age group				
15-29	**3.35**	28.51	**-5.56**	0.00
30-44	**2.29**	9.83	**-4.54**	0.01
45-54	0.18	1.19	**-5.21**	0.01
Ethnicity				
Māori	**-1.24**	0.29	**1.53**	4.62
Pacific peoples	**-1.96**	0.14	0.61	1.83
Education				
Access to a motor vehicle				
No motor vehicle	**0.78**	2.19	-0.61	0.54
Household income				
Socioeconomic deprivation				

Key: Values highlighted in bold indicate statistically significant association

5.5 Results –Network buffer

Model One

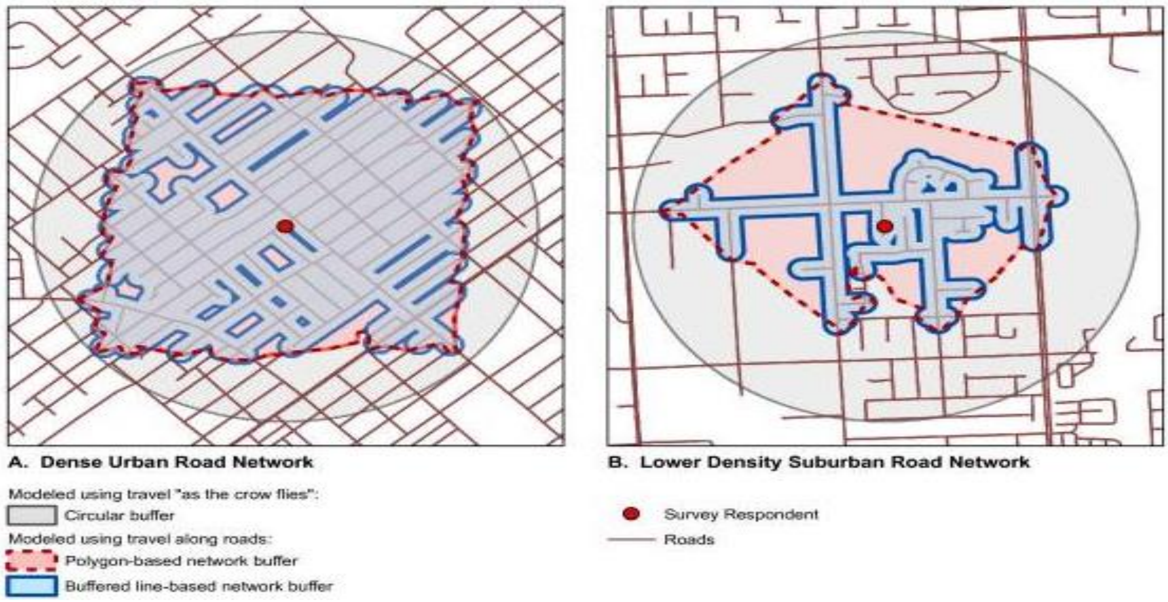
The network analysis (Table 10) indicates that there is no statistically significant association between active travel and walkability, which may be due to the use of polygon-based network buffers instead of buffered line-based network buffers (example shown below in Figure 32).

Table 10. Network model one - Unadjusted

	Count model		Zero-inflated model	
Variable	**Estimate**	**Exponetiated coefficients**	**Estimates**	**Exponetiated coefficients**
Intercept	**-**	-	**-**	-
Walkability index				
Buffer800m	**-0.03**	-	**-**	-

Key: Values highlighted in bold indicate statistically significant associations

The results are consistent with research by Oliver et al. (2007), which showed that in numerous models, there was a higher association between the built environment and walking when using the line-based road network buffer instead of the polygon-based method. This suggests that line-based buffers may be more sensitive than polygon buffers to detect associations with walking.



Source: (Oliver et al., 2007)

Figure 32. Comparison of buffer methods for assessing neighbourhood land use

Chapter 6: Walkability Index and Adolescent Depression

To compare the estimated walkability of the Wellington Region and depression, a self-reported measure of the severity of depressive symptoms (radssf) was obtained from the Youth'12 National Youth Health Survey. The measure was then compared to the Euclidean-based walkability index (Walk800mBuffer) using the PROC SURVEYREG procedure in SAS (9.2). The two datasets were merged using the meshblock ID; resulting in a dataset of 419 unique cases, (incomplete cases were excluded). The data obtained from the Youth'12 National Youth Health Survey contains basic demographic information on the survey participant as well as the cluster (schoolid to account for school clustering) and weight variables (Weighting). Sex (Intro2) was coded 1=male and 2=female, and age (Intro1) was coded as a continuous variable. Prioritised ethnicity (ethnic_p5) and household poverty (ses) were also included in the analysis. Household poverty was based on nine indicators of household socioeconomic deprivation (no car; no phone; no computer; their parent/s worry about not having enough money for food; more than two people sharing a bedroom; no holidays with their families; moving home more than twice that year; garages or living rooms used as bedrooms; and, no parent at home with employment). The variable was measured as a binary variable where 1 represented two or more poverty items, while zero represented less than two.

Table 11. Summary of data

Data Summary	
Number of observations	419
Sum of weights	2070.1
Weighted Mean of radssf	20.1
Weighted sum of radssf	41554.5
Design summary	
Number of clusters	7
Fit Statistic	
R-squared	0.15
Root MSE	6.41
Denominator DF	6

Table 11 shows the data summary, with 419 observations analysed and a weighted mean of 20.07. The summary shows that the study contained seven school clusters and the fit statistic indicates that the model explains 15% of the variability in the data.

Descriptive Statistics

Table 12 is a summary of the socio-demographic characteristics of the Youth'12 National Youth Health Survey data. There were 419 students included in the Wellington region sample. The sample consisted of 54% females and 46% males and was composed of five main age groups. The age with the lowest percentage of students was 18 (5.8%), followed by 17 (14.6%) and 16 (17.2%). The majority of students were either aged 13(20.3%), 14(20.3%) or 15(22%). In terms of ethnicity, the majority of students were in the European (33.4%) ethnic group, followed by Maori (23.0%), Asian (14.0%), Pacific (17.0%) and Other (9.0%). Relating to household poverty, 77.1% of students had less than two poverty items, while 23.0% had two or more poverty items. Overall, the table also shows that 16.7% of the students had RADS test scores that were over 77, indicating that clinically significant depression may be present.

Table 12. Socio-demographic characteristics of Youth'12 National Youth Health Survey study participants

Variable	**N (%)**
Sex	
Male	**192 (46.0%)**
Female	**227 (54.0%)**
Age	
13	**85 (20.3%)**
14	**85 (20.3%)**
15	**92 (22%)**
16	**72 (17.2%)**
17	**61 (14.6%)**
18	**24 (5.8%)**
Ethnicity	
European	**161 (33.4%)**
Maori	**95 (23.0%)**
Pacific	**69 (17.0%)**
Asian	**58 (14.0%)**
Other	**36 (9.0%)**
Household poverty	
Less than two poverty items	**323 (77.1%)**
Two or more poverty items	**96 (23.0%)**
Test scores below 77	**349 (83.3%)**
Test scores of over 77	**70 (16.7%)**

The summary presented in Table 13 is a comparison of the socio-demographic characteristics of students who had RADS scores below 77 and those who had scores above 77. A comparison of scores by sex indicates that Females had the highest percentage of scores above 77 (78.1% vs 21.4%), however in terms of score below 77, both Male and females had similar percentages. In terms of age, there was little difference between the percentages for scores under 77 and over 77. The European (35.7%) ethnic group had the highest percentage of students who had RADS scores above 77, followed by the Māori ethnic group (25.7%). Interestingly, students with the lowest number of poverty items had the highest percentage of scores over 77 (57.1%). This was also the case for scores under 77 (81.1%).

Table 13. Socio-demographic characteristics of Youth'12 National Youth Health Survey study participants by health-related variables.

Variable		More than 77 score N (%)	Less than 77 score N (%)
Sex			
	Male	**15(21.4%)**	**177 (50.7%)**
	Female	**55 (78.1%)**	**172 (49.3%)**
Age			
	13	**11 (15.7%)**	**74 (21.2%)**
	14	**17 (24.3%)**	**68 (19.5%)**
	15	**17 (24.3%)**	**75 (21.5%)**
	16	**14 (20.0%)**	**58 (16.6%)**
	17	**7 (10.0%)**	**54 (15.5%)**
	18	**4 (5.7%)**	**20 (5.7%)**
	Ethnicity		
	European	**25 (35.7%)**	**136 (39.0%)**
	Maori	**18 (25.7%)**	**77 (22.1%)**
	Pacific	**11 (15.7%)**	**58 (16.65)**
	Asian	**11 (15.7%)**	**47 (13.5%)**
	Other	**5 (7.1%)**	**31 (8.9%)**
	Household poverty		
	Less than two poverty items	**40 (57.1%)**	**283 (81.1%)**
	Two or more poverty items	**30 (42.9%)**	**66 (18.9%)**

Associations between walkability and Depression

Table 14. Class level and testing effects

Class Level Information			
CLASS Variable	**Label**	**Levels**	**Values**
Walk800mBuffer	Walk800mBuffer	10	1 2 3 4 5 6 7 8 9 10
Intro2	Intro2	2	1 2
ethnic_p5	ethnic_p5	5	Asian European Māori Other Pacific
ses	ses	2	
Tests of Model Effects			
Effect	**Num DF**	**F Value**	**Pr > F**
Model	6	7.59	0.0131
Intercept	1	471.46	<.0001
Walk800mBuffer	6	12.87	0.0034
Intro1	1	0.85	0.3927
Intro2	1	15.12	0.0081
ethnic_p5	4	6.85	0.0201
ses	1	10.65	0.0172

Table 12 shows that the overall model is significant (0.01), Walkability was also shown to be significant at the 1% level while controlling for age, sex, ethnicity and number of poverty items. This means we can reject the null hypothesis that walkability does not affect adolescent depression. The results also indicate that household poverty and sex are significant, suggesting that they have an influence on adolescent depression.

Chapter 7: Discussion

This research investigated the relationship between walkability, active travel and adolescent depression. A composite walkability index was developed consisting of various attributes of the built environment such as intersection density, land-use mix, mean NDVI, dwelling density and average traffic volume. This chapter summarises the main research findings and methodological contributions and discusses the limitations and strengths of the research and makes recommendations for future research on the effect of the built environment on mental health, particularly adolescents.

Summary of findings

The analysis indicated that the walkability of the built environment is associated with an increased likelihood of active travel to work for the 800m Euclidean buffer. Even after accounting for sex, age and ethnicity, and socioeconomic factors, the association between walkability and active travel to work remained statistically significant both the count and zero-inflated models. Being aged 15-29, 30-44 and 45-54 and being of Māori ethnicity were also statistically significant variables in models 1, 2 and 3, while the 55-64 age group was not statistically significant. These findings indicate that this research was justified in restricting the study population to adolescents as they were shown to be within one of the age-groups most significantly influenced by the walkability of an area. The ethnicity findings indicate that further research is required to determine the differences between Māori and non-Māori, in relation to active travel, the built environment and mental health outcomes.

Regarding the network buffer, findings indicated that there was no statistically significant association between walkability and active travel. However, the findings may be due to the use of polygon-based network buffers instead of buffered line-based network buffers. Also, this may be due to the use of only one spatial scale (i.e. 800m). Previous research has shown that perceptions of the neighbourhood area differ; therefore, two buffer zones (1200m and 1600m) could have been used to test the sensitivity of the 800m neighbourhood area. Such a procedure would have ensured that areas outside of the residential area, where physical activity and active transport behaviours are also conducted were accounted for when measuring the built environment.

In terms of the relationship between walkability and depressive symptoms in adolescents, results showed that living in a walkable area was associated with lower depressive symptoms. In particular, household poverty and sex had a significant influence on depressive symptoms. While the model only explained 15% of the variability in the data, the association between walkability and adolescent depression was significant before and after accounting for demographic and socioeconomic variables.

Similar research conducted in Wellington City by Donnellan (2016) supports the findings in this study, as it found a strong statistically significant positive association between walking and cycling to work and walkability at various neighbourhood levels (800m, 1200m, 1600m). These results remained consistent even after fully adjusting for age, sex, ethnicity, education, household income, household access to a car and a measure of neighbourhood deprivation.

Limitations and strengths of this research

Using a similar methodology to previous NZ research enabled the current research to validate these methods and findings in order to contribute to the built environment research field (Hannah M Badland, Keam, Witten, & Kearns, 2010; Hannah M. Badland et al., 2009; Donnellan, 2016). However, limitations were still present, and this section of the discussion seeks to address them.

A major limitation that arose was the use of meshblocks to construct measures of the built environment. It was found that in some instances pre-defined Census units can be misleading. For instance, some meshblocks in rural areas are geographically very large, which can lead to noteworthy accuracy issues. In particular, the land use variable presented in Figures 6 and 13 showed that smaller meshblocks are typically homogeneous in term of land-use. However, they might be surrounded by heterogeneous meshblocks, resulting in an incorrect interpretation of access to services and facilities. Findings will indicate that adolescents who live in smaller homogeneous meshblocks have limited access to many facilities in their meshblock. However, they can easily walk to the neighbouring heterogeneous meshblocks for access to other facilities. Therefore, even though they live in a homogenous meshblock, they still live in a heterogeneous neighbourhood area. This aspect of the built environment can be difficult to capture, particularly when using pre-defined Census units.

In this study, Network and Euclidean buffers were used to address the MAUP issue by adopting a hybrid method that combined the use of predefined spatial units and the buffering method. While this method is more representative of the neighbourhood environment, it still has some limitations. As mentioned in the summary of findings, previous research has shown that perceptions of the neighbourhood area differ (Cerin, Macfarlane, Ko, & Chan, 2007). Therefore, multiple buffers at various spatial level could be used to ensure that areas outside of the residential area, where physical activity and active transport behaviours are also conducted, are accounted for.

Another major limitation was the lack of information about which particular built environment variables have the most influence on adolescents. This information would have been valuable in assisting in the selection and weighting of variables used in the index, as the parameters used in this study were equally weighted. The validity of this approach is an aspect that future scholars should explore when trying to find methods to optimise walkability modelling.

Overall, the methods used in this research were robust, as the same spatial scale was used for all data sources, reducing the risk of Modifiable Areal Unit Problem (MAUP). Research has shown that the choice of a spatial unit can influence analysis results (Deng & Xu, 2015). Overall, smaller Census units are preferable as they are less averaged and aggregated. In New Zealand, meshblocks are the smallest geographic boundary. Therefore, this thesis employed meshblocks as the geographic neighbourhood boundary for all analysis.

Future research

The built environment can be measured using a wide range of data sources, using a variety of methods and under various characterisations of the environment. One of the many areas to be addressed in the future is the lack of high quality and robust public health data.

While GIS-based walkability indices have improved over the years, the lack of standardisation in their constructed will remains challenging for future researches. (Feng et al., 2010). This lack of standardisation will be challenging for future research, and one of the leading causes of this issue is the lack of national-level data. A possible task for future researches could be to develop a national database for built environment data, which would enable studies to be comparable. The spatial extent, source of data, and the number of places compared across studies is very variable. Currently, no two studies in New Zealand that have evaluated the built environment using the same parameters or areas.

Conclusion

The current study demonstrates an association between walkability and symptoms of depression in adolescents and demonstrates that a walkable neighbourhood may help to reduce depressive symptoms. Further research is required to test the walkability model with measures of depressive symptoms in rural and ethnically diverse locations. The findings presented in this research have implications for clinicians and policymakers. The findings suggest that future research should aim to determine if neighbourhood-level interventions based on characteristics of the built environment might improve health outcomes in adolescents.

Recommendations

Due to adolescents spending a vast majority of their daytime hours in school environments, interventions targeted at adolescents should aim to improve the environments which young people inhabit in order to improve overall mental health outcomes.

References

Abramson, L. Y., Seligman, M. E., & Teasdale, J. D. (1978). Learned helplessness in humans: critique and reformulation. *Journal of abnormal psychology, 87*(1), 49.

Acland Street Precinct Traders, A. (2003). Acland Street Precinct Traders Association-Draft summary of key findings and recommendations. In: Melbourne, Australia.

Adolescent Health Research, G. (2013). The health and wellbeing of New Zealand secondary school students in 2012. *Youth'12 Prevalence Tables*.

Agampatian, R. (2014). *Using GIS to measure walkability: a case study in New York City.* (Master's of Science Thesis in Geoinformatics), KTH Royal Institute of Technology, Stockholm, Sweden. (TRITA-GIT EX 14-002)

Altman, I. (1975). The Environment and Social Behavior: Privacy, Personal Space, Territory, and Crowding.

Anderson, D. R., & Burnham, K. P. (2002). Avoiding pitfalls when using information-theoretic methods. *The Journal of Wildlife Management*, 912-918.

Aneshensel, C. S., & Sucoff, C. A. (1996). The neighborhood context of adolescent mental health. *Journal of health and social behavior*, 293-310.

Angold, A., Costello, E. J., Erkanli, A., & Worthman, C. M. (1999). Pubertal changes in hormone levels and depression in girls. *Psychological medicine, 29*(5), 1043-1053.

ArcGis, E. (2014). 10.2. 2 for Desktop. *Redlands, CA, USA: Environmental Systems Research Institute*.

Badland, H. M., Keam, R., Witten, K., & Kearns, R. (2010). Examining public open spaces by neighborhood-level walkability and deprivation. *Journal of Physical Activity and Health, 7*(6), 818-824.

Badland, H. M., Schofield, G. M., Witten, K., Schluter, P. J., Mavoa, S., Kearns, R. A., . . . Jensen, V. G. (2009). Understanding the Relationship between Activity and Neighbourhoods (URBAN) Study: research design and methodology. *BMC public health, 9*(1), 224.

Baker, M. G., Goodyear, R., Telfar Barnard, L., & Howden-Chapman, P. (2006). *The distribution of household crowding in New Zealand: an analysis based on 1991 to 2006 Census data*: Wellington.

Beaujean, A. A., & Morgan, G. B. (2016). Tutorial on Using Regression Models with Count Outcomes using R. *Practical Assessment, Research & Evaluation, 21*.

Bebbington, P. (1996). The origins of sex differences in depressive disorder: bridging the gap. *International Review of Psychiatry, 8*(4), 295-332.

Berman, M. G., Kross, E., Krpan, K. M., Askren, M. K., Burson, A., Deldin, P. J., . . . Jonides, J. (2012). Interacting with nature improves cognition and affect for individuals with depression. *Journal of affective disorders, 140*(3), 300-305.

Beutel, M. E., Jünger, C., Klein, E. M., Wild, P., Lackner, K., Blettner, M., . . . Brähler, E. (2016). Noise annoyance is associated with depression and anxiety in the general population-the contribution of aircraft noise. *Plos one, 11*(5), e0155357.

Beyer, K. M., Kaltenbach, A., Szabo, A., Bogar, S., Nieto, F. J., & Malecki, K. M. (2014). Exposure to neighborhood green space and mental health: evidence from the survey of the health of Wisconsin. *International journal of environmental research and public health, 11*(3), 3453-3472.

Blazer, D., Burchett, B., Service, C., & George, L. K. (1991). The association of age and depression among the elderly: an epidemiologic exploration. *Journal of gerontology, 46*(6), M210-M215.

Booth, K. M., Pinkston, M. M., & Poston, W. S. C. (2005). Obesity and the Built Environment. *Journal of the American Dietetic Association, 105*(5, Supplement), 110-117. doi:https://doi.org/10.1016/j.jada.2005.02.045

Booth, M. L., Owen, N., Bauman, A., Clavisi, O., & Leslie, E. (2000). Social–cognitive and perceived environment influences associated with physical activity in older Australians. *Preventive medicine, 31*(1), 15-22.

Bouma, E. M. C., Ormel, J., Verhulst, F. C., & Oldehinkel, A. J. (2008). Stressful life events and depressive problems in early adolescent boys and girls: The influence of parental depression, temperament and family environment. *Journal of affective disorders, 105*(1), 185-193.

Broman, C. L., Mavaddat, R., & Hsu, S.-y. (2000). The experience and consequences of perceived racial discrimination: A study of African Americans. *Journal of Black Psychology, 26*(2), 165-180.

Brown, S. C., Mason, C. A., Perrino, T., Lombard, J. L., Martinez, F., Plater-Zyberk, E., . . . Szapocznik, J. (2008). Built environment and physical functioning in Hispanic elders: the role of "eyes on the street". *Environmental health perspectives, 116*(10), 1300.

Brownson, R. C., Hoehner, C. M., Day, K., Forsyth, A., & Sallis, J. F. (2009). Measuring the built environment for physical activity: state of the science. *American journal of preventive medicine, 36*(4), S99-S123.
Campagna, G. (2016). Linking crowding, housing inadequacy, and perceived housing stress. *Journal of Environmental Psychology, 45*, 252-266.
Carter, T., Morres, I. D., Meade, O., & Callaghan, P. (2016). The Effect of Exercise on Depressive Symptoms in Adolescents: A Systematic Review and Meta-Analysis. *Journal of the American Academy of Child & Adolescent Psychiatry, 55*(7), 580-590. doi:10.1016/j.jaac.2016.04.016
Catlin, T. K., Simoes, E. J., & Brownson, R. C. (2003). Environmental and policy factors associated with overweight among adults in Missouri. *American journal of health promotion, 17*(4), 249-258.
Cerin, E., Macfarlane, D. J., Ko, H.-H., & Chan, K.-C. A. (2007). Measuring perceived neighbourhood walkability in Hong Kong. *Cities, 24*(3), 209-217.
Cervero, R. (1989). *America's suburban centers: the land use-transportation link*. Boston, MA: Unwin Hyman.
Chapman, L. (2007). Transport and climate change: a review. *Journal of transport geography, 15*(5), 354-367.
Cheng, A. T., Chen, T. H., Chen, C.-C., & Jenkins, R. (2000). Psychosocial and psychiatric risk factors for suicide: case-control psychological autopsy study. *The British Journal of Psychiatry, 177*(4), 360-365.
Cheung, F. K., & Snowden, L. R. (1990). Community mental health and ethnic minority populations. *Community Mental Health Journal, 26*(3), 277-291.
Clark, T. C., Lucassen, M. F. G., Bullen, P., Denny, S. J., Fleming, T. M., Robinson, E. M., & Rossen, F. V. (2014). The health and well-being of transgender high school students: results from the New Zealand adolescent health survey (Youth'12). *Journal of Adolescent Health, 55*(1), 93-99.
Collins, J., Ward, B. M., Snow, P., Kippen, S., & Judd, F. (2017). Compositional, contextual, and collective community factors in mental health and well-being in Australian rural communities. *Qualitative health research, 27*(5), 677-687.
De Vries, S., Verheij, R. A., Groenewegen, P. P., & Spreeuwenberg, P. (2003). Natural environments—healthy environments? An exploratory analysis of the relationship between greenspace and health. *Environment and planning A, 35*(10), 1717-1731.
Deng, Y., & Xu, H. (2015). International direct investment and transboundary pollution: An empirical analysis of complex networks. *Sustainability, 7*(4), 3933-3957.
Denny, S., Fleming, T., Clark, T. C., & Wall, M. (2004). Emotional resilience: Risk and protective factors for depression among alternative education students in New Zealand. *American Journal of Orthopsychiatry, 74*(2), 137-149.
Denny, S., Lewycka, S., Utter, J., Fleming, T., Peiris-John, R., Sheridan, J., . . . Bullen, P. (2016). The association between socioeconomic deprivation and secondary school students' health: findings from a latent class analysis of a national adolescent health survey. *International journal for equity in health, 15*(1), 109.
Diez Roux, A. V. (2001). Investigating Neighborhood and Area Effects on Health. *American journal of public health, 91*(11), 1783-1789.
Dill, J. (2005). Measuring Network Connectivity for Bicycling and Walking, School of Urban Studies and Planning, Portland State University. *Transportation Research Board 2004 Annual Meeting*.
Donnellan, N. M. (2016). A geospatial approach to measuring the built environment for active transport, physical activity and health outcomes.
Dora, C., Phillips, M. A., & Phillips, M. (2000). *Transport, environment and health*: WHO Regional Office Europe.
Egede, L. E., & Ellis, C. (2010). Diabetes and depression: global perspectives. *Diabetes research and clinical practice, 87*(3), 302-312.
Elisabeth Wells, J., Oakley Browne, M. A., Scott, K. M., McGee, M. A., Baxter, J., Kokaua, J., & New Zealand Mental Health Survey Research, T. (2006). Te Rau Hinengaro: the New Zealand mental health survey: overview of methods and findings. *Australian and New Zealand Journal of Psychiatry, 40*(10), 835-844.
Esteban-Cornejo, I., Carlson, J. A., Conway, T. L., Cain, K. L., Saelens, B. E., Frank, L. D., . . . Sallis, J. F. (2016). Parental and adolescent perceptions of neighborhood safety related to adolescents' physical activity in their neighborhood. *Research quarterly for exercise and sport, 87*(2), 191-199.
Evans, G. W. (2003). The built environment and mental health. *Journal of Urban Health, 80*(4), 536-555.
Evans, G. W., & Lepore, S. J. (1993). Household crowding and social support: A quasiexperimental analysis. *Journal of Personality and Social Psychology, 65*(2), 308.
Evans, G. W., & Stecker, R. (2004). Motivational consequences of environmental stress. *Journal of Environmental Psychology, 24*(2), 143-165.
Ewing, R., & Cervero, R. (2010). Travel and the built environment: a meta-analysis. *Journal of the American planning association, 76*(3), 265-294.

Fairnie, G. A., Wilby, D. J. R., & Saunders, L. E. (2016). Active travel in London: the role of travel survey data in describing population physical activity. *Journal of Transport & Health, 3*(2), 161-172.
Faris, R. E. L., & Dunham, H. W. (1939). Mental disorders in urban areas: an ecological study of schizophrenia and other psychoses.
Feng, J., Glass, T. A., Curriero, F. C., Stewart, W. F., & Schwartz, B. S. (2010). The built environment and obesity: a systematic review of the epidemiologic evidence. *Health & place, 16*(2), 175-190.
Firdaus, G. (2017). Built environment and health outcomes: Identification of contextual risk factors for mental well-being of older adults. *Ageing International, 42*(1), 62-77.
Flowerdew, R., Manley, D. J., & Sabel, C. E. (2008). Neighbourhood effects on health: Does it matter where you draw the boundaries? *Social science & medicine, 66*(6), 1241-1255. doi:https://doi.org/10.1016/j.socscimed.2007.11.042
Forsyth, A., Schmitz, K. H., Oakes, M., Zimmerman, J., & Koepp, J. (2006). Standards for environmental measurement using GIS: toward a protocol for protocols. *Journal of Physical Activity and Health, 3*(s1), S241-S257.
Forsyth, A., & Southworth, M. (2008). Cities afoot—Pedestrians, walkability and urban design.
Frank, L., Kerr, J., Saelens, B., Sallis, J., Glanz, K., & Chapman, J. (2009). Food outlet visits, physical activity and body weight: variations by gender and race–ethnicity. *British Journal of Sports Medicine, 43*(2), 124-131.
Frank, L. D., & Pivo, G. (1994). Impacts of mixed use and density on utilization of three modes of travel: single-occupant vehicle, transit, and walking.
Fridell, E. J., Öjehagen, A., & Träskman-Bendz, I. (1996). A 5-year follow-up study of suicide attempts. *Acta Psychiatrica Scandinavica, 93*(3), 151-157.
Gable, S. L., Reis, H. T., & Elliot, A. J. (2000). Behavioral activation and inhibition in everyday life. *Journal of Personality and Social Psychology, 78*(6), 1135.
Giles-Corti, B., & Donovan, R. J. (2002). The relative influence of individual, social and physical environment determinants of physical activity. *Social science & medicine, 54*(12), 1793-1812.
Gladstone, T. R., Kaslow, N. J., Seeley, J. R., & Lewinsohn, P. M. (1997). Sex differences, attributional style, and depressive symptoms among adolescents. *Journal of Abnormal Child Psychology, 25*(4), 297-306.
Gomez-Jacinto, L., & Hombrados-Mendieta, I. (2002). Multiple effects of community and household crowding. *Journal of Environmental Psychology, 22*(3), 233-246.
Gove, W. R., Hughes, M., & Galle, O. R. (1979). Overcrowding in the home: An empirical investigation of its possible pathological consequences. *American sociological review*, 59-80.
Grimes, A., Maré, D. C., Morten, M., & Maré, D. *Defining Areas: Linking Geographic Data in New Zealand*. Citeseer.
Halpern, D. (2014). *Mental health and the built environment: more than bricks and mortar?* : Routledge.
Handy, S. L., Boarnet, M. G., Ewing, R., & Killingsworth, R. E. (2002). How the built environment affects physical activity: views from urban planning. *American journal of preventive medicine, 23*(2), 64-73.
Hart, J., & Parkhurst, G. (2011). Driven to excess: Impacts of motor vehicles on the quality of life of residents of three streets in Bristol UK. *World Transport Policy & Practice, 17*(2), 12-30.
Haynes, R. B., Ackloo, E., Sahota, N., McDonald, H. P., & Yao, X. (2008). Interventions for enhancing medication adherence. *Cochrane Database of Systematic Reviews*(2). doi:10.1002/14651858.CD000011.pub3
Heidemann, C., Niemann, H., Paprott, R., Du, Y., Rathmann, W., & Scheidt-Nave, C. (2014). Residential traffic and incidence of type 2 diabetes: the German Health Interview and Examination Surveys. *Diabetic Medicine, 31*(10), 1269-1276.
Hester, R. T. (1984). *Planning neighborhood space with people (Vol. 3)*: Van Nostrand Reinhold.
Hirschfeld, R., Montgomery, S. A., Keller, M. B., Kasper, S., Schatzberg, A. F., Möller, H.-J., . . . Versiani, M. (2000). Social functioning in depression: a review. *The Journal of clinical psychiatry*.
Huebner, E. S. (1991). Initial development of the student's life satisfaction scale. *School Psychology International, 12*(3), 231-240.
Huynh, Q., Craig, W., Janssen, I., & Pickett, W. (2013). Exposure to public natural space as a protective factor for emotional well-being among young people in Canada. *BMC public health, 13*(1), 407. doi:10.1186/1471-2458-13-407
Hyde, J. S., Mezulis, A. H., & Abramson, L. Y. (2008). The ABCs of depression: integrating affective, biological, and cognitive models to explain the emergence of the gender difference in depression. *Psychological review, 115*(2), 291.
Johnson, A., Kirk, R., Rosenblum, K. L., & Muzik, M. (2015). Enhancing breastfeeding rates among African American women: A systematic review of current psychosocial interventions. *Breastfeeding Medicine, 10*(1), 45-62.

Joiner Jr, T. E., & Wagner, K. D. (1995). Attributional style and depression in children and adolescents: A meta-analytic review. *Clinical Psychology Review, 15*(8), 777-798.
Jorm, A. F. (2000). Does old age reduce the risk of anxiety and depression? A review of epidemiological studies across the adult life span. *Psychological medicine, 30*(1), 11-22.
Karsten, L. (2005). It all used to be better? Different generations on continuity and change in urban children's daily use of space. *Child Geogr, 3*. doi:10.1080/14733280500352912
Kessler, R. C., McGonagle, K. A., Zhao, S., & et al. (1994). Lifetime and 12-month prevalence of dsm-iii-r psychiatric disorders in the united states: Results from the national comorbidity survey. *Archives of general psychiatry, 51*(1), 8-19. doi:10.1001/archpsyc.1994.03950010008002
Kessler, R. C., McGonagle, K. A., Zhao, S., Nelson, C. B., Hughes, M., Eshleman, S., . . . Kendler, K. S. (1994). Lifetime and 12-month prevalence of DSM-III-R psychiatric disorders in the United States: results from the National Comorbidity Survey. *Archives of general psychiatry, 51*(1), 8-19.
King, A. C., Castro, C., Wilcox, S., Eyler, A. A., Sallis, J. F., & Brownson, R. C. (2000). Personal and environmental factors associated with physical inactivity among different racial–ethnic groups of US middle-aged and older-aged women. *Health psychology, 19*(4), 354.
Kisely, S., Alichniewicz, K. K., Black, E. B., Siskind, D., Spurling, G., & Toombs, M. (2017). The prevalence of depression and anxiety disorders in indigenous people of the Americas: a systematic review and meta-analysis. *Journal of psychiatric research, 84*, 137-152.
Klebanov, P. K., Brooks-Gunn, J., & Duncan, G. J. (1994). Does neighborhood and family poverty affect mothers' parenting, mental health, and social support? *Journal of Marriage and the Family*, 441-455.
Kneeshaw-Price, S. H., Saelens, B. E., Sallis, J. F., Frank, L. D., Grembowski, D. E., Hannon, P. A., . . . Chan, K. G. (2015). Neighborhood crime-related safety and its relation to children's physical activity. *Journal of Urban Health, 92*(3), 472-489.
Koohsari, M. J., Badland, H., Sugiyama, T., Mavoa, S., Christian, H., & Giles-Corti, B. (2015). Mismatch between perceived and objectively measured land use mix and street connectivity: associations with neighborhood walking. *Journal of Urban Health, 92*(2), 242-252.
Kupfer, D. J. (2014). Depression and the new DSM-5 classification. *Medicographia, 34*, 521-525.
Landry, N., Gifford, R., Milfont, T. L., Weeks, A., & Arnocky, S. (2018). Learned helplessness moderates the relationship between environmental concern and behavior. *Journal of Environmental Psychology, 55*, 18-22.
Lee, A. C., & Maheswaran, R. (2011). The health benefits of urban green spaces: a review of the evidence. *Journal of public health, 33*(2), 212-222.
Lee, A. C. K., Jordan, H. C., & Horsley, J. (2015). Value of urban green spaces in promoting healthy living and wellbeing: prospects for planning. *Risk management and healthcare policy, 8*, 131.
Lee, C. H., Duck, I. M., & Sibley, C. G. (2017). Ethnic inequality in diagnosis with depression and anxiety disorders.
Lepore, S. J., Evans, G. W., & Schneider, M. L. (1991). Dynamic role of social support in the link between chronic stress and psychological distress. *Journal of Personality and Social Psychology, 61*(6), 899.
Li, F., Harmer, P. A., Cardinal, B. J., Bosworth, M., Acock, A., Johnson-Shelton, D., & Moore, J. M. (2008). Built environment, adiposity, and physical activity in adults aged 50–75. *American journal of preventive medicine, 35*(1), 38-46.
Maria Kockelman, K. (1997). Travel behavior as function of accessibility, land use mixing, and land use balance: evidence from San Francisco Bay Area. *Transportation research record, 1607*(1), 116-125.
Mavoa, S., Eagleson, S., Badland, H. M., Gunn, L., Boulange, C., Stewart, J., & Giles-Corti, B. (2018). Identifying appropriate land-use mix measures for use in a national walkability index. *Journal of Transport and Land Use, 11*(1).
Mavoa, S., Witten, K., Pearce, J., & Day, P. (2009). Measuring neighbourhood walkability in New Zealand cities. *Centre for Social and Health Outcomes Research and Evaluation, Massey University, Auckland*.
McCaffrey, R., Hanson, C., & McCaffrey, W. (2010). Garden walking for depression: a research report. *Holistic nursing practice, 24*(5), 252-259.
McCarthy, L., Delbosc, A., Currie, G., & Molloy, A. (2017). Factors influencing travel mode choice among families with young children (aged 0–4): a review of the literature. *Transport reviews, 37*(6), 767-781.
Mckenzie, S. K., Carter, K., Blakely, T., & Collings, S. (2010). The association of childhood socio-economic position and psychological distress in adulthood: is it mediated by adult socio-economic position? *Longitudinal and life course studies, 1*(4), 339-358.

McKenzie, S. K., Collings, S., Jenkin, G., & River, J. (2018). Masculinity, Social Connectedness, and Mental Health: Men's Diverse Patterns of Practice. *American Journal of Men's Health, 12*(5), 1247-1261. doi:10.1177/1557988318772732
Melis, G., Gelormino, E., Marra, G., Ferracin, E., & Costa, G. (2015). The effects of the urban built environment on mental health: A cohort study in a large northern Italian city. *International journal of environmental research and public health, 12*(11), 14898-14915.
Meltzer, H., Gill, B., Petticrew, M., & Hinds, K. (1995). OPCS surveys of psychiatric morbidity in Great Britain. *Report, 1*, 16-64.
Mezulis, A. H., Funasaki, K. S., Charbonneau, A. M., & Hyde, J. S. (2010). Gender differences in the cognitive vulnerability-stress model of depression in the transition to adolescence. *Cognitive Therapy and Research, 34*(6), 501-513.
Miles, R., Coutts, C., & Mohamadi, A. (2012). Neighborhood urban form, social environment, and depression. *Journal of Urban Health, 89*(1), 1-18.
Ministry of Health. (2017). *Annual update of key results 2016/17: New Zealand health survey*. Ministry of Health Wellington.
Ministry of Transport. (2017). New Zealand Household Travel Survey 2015-2017. Retrieved 9/10/2018 from https://www.transport.govt.nz/assets/Uploads/Research/Documents/Household-Travel-Survey-intro-Dec2017.pdf
Mirowsky, J., & Ross, C. E. (1992). Age and depression. *Journal of health and social behavior*, 187-205.
Mujahid, M. S., Diez Roux, A. V., Morenoff, J. D., Raghunathan, T. E., Cooper, R. S., Ni, H., & Shea, S. (2008). Neighborhood Characteristics and Hypertension. *Epidemiology, 19*(4), 590-598. doi:10.1097/EDE.0b013e3181772cb2
Mutrie, N. (2003). The relationship between physical activity and clinically defined depression. *Physical activity and psychological well-being*, 58-72.
Niemann, H., Maschke, C., & Hecht, K. (2005). Noise induced annoyance and morbidity. Results from the pan European LARES-survey. *Bundesgesundheitsblatt, Gesundheitsforschung, Gesundheitsschutz, 48*(3), 315-328.
Nolen-Hoeksema, S., Girgus, J. S., & Seligman, M. E. (1992). Predictors and consequences of childhood depressive symptoms: A 5-year longitudinal study. *Journal of abnormal psychology, 101*(3), 405.
Nowicka-Sauer, K., Hajduk, A., Kujawska-Danecka, H., Banaszkiewicz, D., Czuszyńska, Z., Smoleńska, Ż., & Siebert, J. (2017). Learned helplessness and its associations with illness perception, depression and anxiety among patients with systemic lupus erythematosus. *Family Medicine & Primary Care Review, 19*(3), 243-246. doi:10.5114/fmpcr.2017.69285
Nutsford, D., Pearson, A., & Kingham, S. (2013). An ecological study investigating the association between access to urban green space and mental health. *Public health, 127*(11), 1005-1011.
Oliver, L. N., Schuurman, N., & Hall, A. W. (2007). Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands. *International journal of health geographics, 6*(1), 41.
Pearce, J., Hiscock, R., Blakely, T., & Witten, K. (2008). The contextual effects of neighbourhood access to supermarkets and convenience stores on individual fruit and vegetable consumption. *Journal of Epidemiology & Community Health, 62*(3), 198-201.
Pearce, J., Witten, K., & Bartie, P. (2006). Neighbourhoods and health: a GIS approach to measuring community resource accessibility. *Journal of Epidemiology and Community Health, 60*(5), 389-395. doi:10.1136/jech.2005.043281
Pepin, C., Muckle, G., Moisan, C., Forget-Dubois, N., & Riva, M. (2018). Household overcrowding and psychological distress among Nunavik Inuit adolescents: a longitudinal study. *International journal of circumpolar health, 77*(1), 1541395.
Poulton, R., Caspi, A., Milne, B. J., Thomson, W. M., Taylor, A., Sears, M. R., & Moffitt, T. E. (2002). Association between children's experience of socioeconomic disadvantage and adult health: a life-course study. *The lancet, 360*(9346), 1640-1645.
Qgis Development Team. (2016). QGIS geographic information system. *Open Source Geospatial Foundation Project*.
Read, J. (2010). Can poverty drive you mad?'Schizophrenia', socio-economic status and the case for primary prevention. *New Zealand Journal of Psychology (Online), 39*(2), 7.
Reeves, G. M., Postolache, T. T., & Snitker, S. (2008). Childhood obesity and depression: connection between these growing problems in growing children. *International journal of child health and human development: IJCHD, 1*(2), 103.
Reynolds, W. M. (2010). Reynolds adolescent depression scale. *The Corsini Encyclopedia of Psychology*, 1-1.

Rhew, I. C., Vander Stoep, A., Kearney, A., Smith, N. L., & Dunbar, M. D. (2011). Validation of the normalized difference vegetation index as a measure of neighborhood greenness. *Annals of epidemiology, 21*(12), 946-952.
Richardson, E. A., Pearce, J., Mitchell, R., & Kingham, S. (2013). Role of physical activity in the relationship between urban green space and health. *Public health, 127*(4), 318-324.
Riedel, N., Köckler, H., van Kamp, I., Scheiner, J., Erbel, R., Loerbroks, A., . . . Bolte, G. (2018). Perceived noise control and its value in the association of road traffic noise with noise annoyance: Natalie Riedel. *European Journal of Public Health, 28*(suppl_4), cky213-317.
Riolo, S. A., Nguyen, T. A., Greden, J. F., & King, C. A. (2005). Prevalence of depression by race/ethnicity: findings from the National Health and Nutrition Examination Survey III. *American journal of public health, 95*(6), 998-1000.
Ross, C. E., & Sastry, J. (1999). The sense of personal control. In *Handbook of the sociology of mental health* (pp. 369-394): Springer.
RStudio Team. (2015). RStudio: integrated development for R. *RStudio, Inc., Boston, MA URL http://www. rstudio. com, 42*, 14.
Saarloos, D., Alfonso, H., Giles-Corti, B., Middleton, N., & Almeida, O. P. (2011). The built environment and depression in later life: the health in men study. *The American Journal of Geriatric Psychiatry, 19*(5), 461-470.
Sadock, B., & Ruiz, P. (2015). *Kaplan & Sadock's synopsis of psychiatry: behavioral sciences*: Walters Kluwer.
Saegert, S. (1982). Environment and children's mental health: Residential density and low income children. *Handbook of psychology and health, 2*, 247-271.
Salk, R. H., Hyde, J. S., & Abramson, L. Y. (2017). Gender differences in depression in representative national samples: Meta-analyses of diagnoses and symptoms. *Psychological Bulletin, 143*(8), 783.
Sallis, J. F., Saelens, B. E., Frank, L. D., Conway, T. L., Slymen, D. J., Cain, K. L., . . . Kerr, J. (2009). Neighborhood built environment and income: examining multiple health outcomes. *Social science & medicine, 68*(7), 1285-1293.
Salze, P., Banos, A., Oppert, J.-M., Charreire, H., Casey, R., Simon, C., . . . Weber, C. (2011). Estimating spatial accessibility to facilities on the regional scale: an extended commuting-based interaction potential model. *International journal of health geographics, 10*(1), 2. doi:10.1186/1476-072x-10-2
Saw, L. E., Lim, F. K. S., & Carrasco, L. R. (2015). The relationship between natural park usage and happiness does not hold in a tropical city-state. *Plos one, 10*(7), e0133781.
Schaakxs, R., Comijs, H. C., van der Mast, R. C., Schoevers, R. A., Beekman, A. T., & Penninx, B. W. (2017). Risk factors for depression: differential across age? *The American Journal of Geriatric Psychiatry, 25*(9), 966-977.
Schweitzer, L., & Su, W.-H. (1977). Population density and the rate of mental illness. *American journal of public health, 67*(12), 1165-1172.
Smith, C. A., Smith, C. J., Kearns, R. A., & Abbott, M. W. (1993). Housing stressors, social support and psychological distress. *Social science & medicine, 37*(5), 603-612.
Song, Y., Merlin, L., & Rodriguez, D. (2013). Comparing measures of urban land use mix. *Computers, Environment and Urban Systems, 42*, 1-13.
Southworth, M. (2005). Designing the walkable city. *Journal of urban planning and development, 131*(4), 246-257.
Stansfeld, S., Haines, M., Burr, M., Berry, B., & Lercher, P. (2000). A review of environmental noise and mental health. *Noise and Health, 2*(8), 1.
Statistics New Zealand. (2013). 2013 Census regional summary tables. Retrieved 04/03/2019 2019 from http://archive.stats.govt.nz/Census/2013-census/data-tables/regional-summary-tables-part-1.aspx
Statistics New Zealand. (2017). Subnational population estimates at 30 June 2017. *Excel Tables). Wellington, New Zealand: Statistics New Zealand.* Retrieved 11 October 2018 from http://archive.stats.govt.nz/browse_for_stats/population/estimates_and_projections/SubnationalPopulationEstimates_HOTPAtJun17.aspx
Statistics New Zealand. (2019). Defining Urban and Rural New Zealand. Retrieved 4/03/2019 2019 from http://archive.stats.govt.nz/browse_for_stats/Maps_and_geography/Geographic-areas/urban-rural-profile/defining-urban-rural-nz.aspx
Stockton, J. C., Duke-Williams, O., Stamatakis, E., Mindell, J. S., Brunner, E. J., & Shelton, N. J. (2016). Development of a novel walkability index for London, United Kingdom: cross-sectional application to the Whitehall II Study. *BMC public health, 16*(1), 416.
Stokols, D. (1996). Translating social ecological theory into guidelines for community health promotion. *American journal of health promotion, 10*(4), 282-298.

Sundquist, K., Frank, G., & Sundquist, J. (2004). Urbanisation and incidence of psychosis and depression: follow-up study of 4.4 million women and men in Sweden. *The British Journal of Psychiatry, 184*(4), 293-298.
Thapar, A., Collishaw, S., Pine, D. S., & Thapar, A. K. (2012). Depression in adolescence. *Lancet, 379*(9820), 1056-1067. doi:10.1016/S0140-6736(11)60871-4
Tiatia-Seath, J. (2014). Pacific peoples, mental health service engagement and suicide prevention in Aotearoa New Zealand. *Ethnicity and inequalities in health and social care, 7*(3), 111-121.
Tresidder, M. (2005). Using GIS to measure connectivity: An exploration of issues. *Portland State University: Field Area Paper*.
Turner, R. J., Wheaton, B., & Lloyd, D. A. (1995). The epidemiology of social stress. *American sociological review*, 104-125.
van Ginneken, E. F. J. C., Sutherland, A., & Molleman, T. (2017). An ecological analysis of prison overcrowding and suicide rates in England and Wales, 2000–2014. *International journal of law and psychiatry, 50*, 76-82.
Van Holle, V., Van Cauwenberg, J., Van Dyck, D., Deforche, B., Van de Weghe, N., & De Bourdeaudhuij, I. (2014). Relationship between neighborhood walkability and older adults’ physical activity: results from the Belgian Environmental Physical Activity Study in Seniors (BEPAS Seniors). *International Journal of Behavioral Nutrition and Physical Activity, 11*(1), 110.
Vanaken, G.-J., & Danckaerts, M. (2018). Impact of Green Space Exposure on Children’s and Adolescents’ Mental Health: A Systematic Review. *International journal of environmental research and public health, 15*(12), 2668.
Waisel, D. B. (2013). Vulnerable populations in healthcare. *Current Opinion in Anesthesiology, 26*(2), 186-192.
Ward, J. S., Duncan, J. S., Jarden, A., & Stewart, T. (2016). The impact of children's exposure to greenspace on physical activity, cognitive development, emotional wellbeing, and ability to appraise risk. *Health & place, 40*, 44-50.
Wei, Y., Xiao, W., Wen, M., & Wei, R. (2016). Walkability, land use and physical activity. *Sustainability, 8*(1), 65.
Wilbur, J., Zenk, S., Wang, E., Oh, A., McDevitt, J., Block, D., . . . Ju, S. (2009). Neighborhood characteristics, adherence to walking, and depressive symptoms in midlife African American women. *Journal of Women's Health, 18*(8), 1201-1210.
Wilkinson, D. (1999). *Poor housing and ill health: a summary of research evidence* (No. 0748079076). Scottish Office.
Wong, D. (2009). The modifiable areal unit problem (MAUP). *The SAGE handbook of spatial analysis*, 105-123.
World Health Organization. (2017). Depression and other common mental disorders: global health estimates.
Yang, T.-C., & Matthews, S. A. (2010). The role of social and built environments in predicting self-rated stress: A multilevel analysis in Philadelphia. *Health & place, 16*(5), 803-810. doi:10.1016/j.healthplace.2010.04.005
Zuur, A. F., & Ieno, E. N. (2016). *Beginner's guide to zero-inflated models with R*: Highland Statistics Limited Newburgh.

Appendix

Table 15.Euclidean model two – Adjusted for demographics (Appendix)

	Count model		Zero-inflated model	
Variable	**Estimate**	**Exponetiated coefficients**	**Estimates**	**Exponetiated coefficients**
Intercept	-0.05	0.95	1.15	3.16
Walkability index				
Buffer800m	**0.10**	1.10	**-0.11**	0.90
Sex				
Male	1.07	2.91	3.42	30.64
Female	1.26	3.53	1.46	4.31
Age group				
15-29	**3.60**	36.75	**-5.65**	0.00
30-44	**2.47**	11.87	**-4.33**	0.01
45-54	0.27	1.30	**-5.17**	0.01
55-64	1.10	3.00	-1.27	0.28
Ethnicity				
Māori	**-1.69**	0.18	1.29	3.14
Pacific peoples	**-2.16**	0.12	0.76	2.14
Asian	-1.11	0.33	-1.86	0.16
European/ Other	-0.95	0.39	-1.84	0.43

Table 16. Euclidean model three - Adjusted for socioeconomic and deprivation (Appendix)

	Count model		Zero-inflated model	
Variable	Estimate	Exponetiated coefficients	Estimates	Exponetiated coefficients
Intercept	-0.56	0.57	1.44	4.22
Walkability Index				
Buffer800m	**0.08**	1.09	**-0.11**	0.89
Sex				
Male	1.34	3.81	3.70	0.52
Female	1.37	3.95	1.70	5.49
Age group				
15-29	**3.35**	28.51	**-5.56**	0.00
30-44	**2.29**	9.83	**-4.54**	0.01
45-54	0.18	1.19	**-5.21**	0.01
55-64	0.96	2.61	-1.89	0.15
Ethnicity				
Māori	**-1.24**	0.29	**1.53**	4.62
Pacific peoples	**-1.96**	0.14	0.61	1.83
Asian	-1.07	0.34	-1.79	0.17
European/ Other	-0.70	0.50	-0.95	0.39
Education				
No qualification	-0.17	0.85	0.70	2.02
High school qualification	-0.24	0.79	0.59	1.80
Post high school diploma or trade certificate	-0.15	0.86	0.67	1.95
Undergraduate university degree	0.52	1.68	0.87	2.38
postgraduate university degree	0.04	1.04	0.24	1.27
Access to a motor vehicle				
No motor vehicle	**0.78**	2.19	-0.61	0.54
One motor vehicle	0.12	1.13	-0.43	0.65
Two motor vehicles	0.06	1.06	-0.25	0.78
Three or more motor vehicles	-0.28	0.75	0.20	1.22
Household income				
20001 - 30000	-0.19	0.83	-1.15	0.32
30001 - 50000	-0.22	0.80	-0.39	0.68
50001 - 70000	0.17	1.19	0.06	1.06
70001 - 100000	-0.02	0.98	-0.31	0.73
100001 or more	0.22	1.25	-0.91	0.40
Socioeconomic deprivation				
NZDep	0.02	1.02	-0.03	0.97