An exploration of the associations between urban natural environments and indicators of mental and physical health.

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February, 2014

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Acknowledgments

I would like to express my gratitude to my supervisory committee for their on-going support and guidance. Prof Simon Kingham, Dr Amber Pearson and Dr Femke Reitsma have been an invaluable source of knowledge and encouragement, without them this thesis would not have been possible.

I thank Simon for first igniting my interest in health geography. His genuine enthusiasm, willingness to help and open-door policy encouraged me to further my academic career. Thanks to Simon I had the opportunity to attend and present at an international conference as well as co-author papers, a rewarding and unexpected bonus during my thesis year.

I thank Amber for her continued support and frighteningly large understanding of statistics. Without it I would have drowned in a sea of confusion. The opportunity to co-author papers with her, as with Simon, was a valuable experience that offered a new understanding of academic research. Amber has been a constant source of support and was always more than willing to offer direction.

I thank Femke for her vast understanding of spatial concepts and technical insight. My gratitude to her goes beyond her supervisory support and I gratefully acknowledge her mentorship over the last two years in the Masters in Geographical Information Systems programme.

I also thank the New Zealand Ministry of Health for funding my thesis year and providing the health data. A special thanks to Edward Griffin for coordinating the exchange of data.

Finally, I thank all of the GeoHealth Laboratory for the positive work environment, the sound advice willingly given and, most importantly, the delectable morning teas.

Abstract

Natural environments, namely green and blue spaces, have been found to have positive influences on mental health outcomes globally. As the contribution of poor mental health to the disease burden increases, the mechanisms through which natural environments may improve health are of growing importance. This study creates a novel visibility index methodology and investigates whether i) views of natural environments and ii) access to natural environments, are associated with psychological stress and physical activity in Wellington, New Zealand. It also builds upon the work conducted in New Zealand as the first study to investigate links between blue space and mental health and provides an insight into the mechanisms through which increased natural environments may improve health.

Individual level data for 442 individuals from the New Zealand Health Survey was obtained and Geographical Information Systems (GIS) were used to investigate whether area-level exposure to natural environments influenced their psychological stress and levels of physical activity. Results from regression analysis indicate that increased distant visible green space (beyond 3km), visible blue space, and a combination of green and blue spaces from neighbourhood centroids reduce psychological stress. Some access measures to natural environments were found to have positive associations with psychological stress, however increased proximal access to green space was associated with decreased physical activity.

The findings conclude that the visibility of natural environments appears to have stronger associations with stress reduction than access to them. The findings of this paper should influence urban development and inform decision and policy making, particularly the development and/or relocation of health related facilities.

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Glossary of terms

Angle of visibility	A measurement in degrees that encapsulates the visual significance of visible areas i.e. incorporates distance, slope, aspect and the elevation of visible areas.
BMI	"Body Mass Index": An individual's body mass divided by the square of their height. Typically a BMI of 25 or above considers the subject to be overweight.
DEM	"Digital Elevation Model": A digital raster representation of the earth's surface where each individual raster cell of a constant area has a unique elevation value.
GIS	"Geographical Information Systems": A system used to capture, store, manipulate, analyse, manage and present geographical data.
Kessler Psychological Stress Scale (K10)	A scale developed in 1992 which uses 10 simple questions to monitor levels of psychological stress for large populations. It is also an instrument to identify likely cases of anxiety and/or depression, the leading causes of poor mental health.
LoS	"Line of Sight": A straight line along which an observer has unobstructed vision.
Meshblock (MB)	New Zealand's smallest administrative boundary, and home to (on average) 100 people. In this study, due to the urban setting, the term 'meshblocks' are synonymous with neighbourhoods.
MOH	"Minsitry of Health": A New Zealand governmental department through which funding for health services is channelled.

Natural environments	Natural environments pertain to i) green spaces, natural or man-made areas of greenery such as native forests, bush reserves, riparian zones, sports grounds and parks, and ii) blue spaces, or aquatic environments including oceans, estuaries, lakes and wide rivers sections.
NZHS	"New Zealand Health Survey": A national survey conducted in 2011/12 that covers population health for a representative sample of NZ residents. The psychological stress and physical activity indicators were obtained through this survey.
Vertical angle	The angle between an observer's eye ball and the top edge and bottom edge of a visible raster cell.
Viewscape	A new generation of visibility analysis which express visibility in a three-dimensional sphere, and incorporates the vertical nature of terrain.
Visible landscape	Typically refers to a view over a large area of land or water and incorporates both the natural and man-made features
Visual significance	Term that encapsulates the significance a visual object has from the perspective of a human. For example steep slopes are more significant in a visualscape than flat areas.
WHO	"World Health Organization": A specialised agency of the United Nations which is concerned with international public health.
VI	"Visibility Index": The visibility index created in this study. While in this study the technique is specific to Wellington, it can be applied to any location.

Chapter 1: Introduction

1.1 General overview

Throughout the ages, human settlement and development has been largely based on the geographic distribution of natural features such as rivers, lakes, coastal environments and forests, which has led to an intrinsic connection between humans and natural environments (Kellert, 2005). The benefits of this connection have long been taken for granted, however now in the 21st century, an increasing body of evidence suggests the presence of these natural environments within urban settings is beneficial towards human health (Maas, Verheij, Groenewegen, de Vries, & Spreeuwenberg, 2006).

In the late 19th century the movement of rural peoples into the cities of America was the first sign of a global migration, now known as urbanisation. Identified as the greatest demographic shift worldwide by Galea & Vlahov (2005), urbanisation represented, and continues to represent, a major transition from the way humans had lived for the previous thousands of years. As the process continues today, the natural environments that played such a significant role in the evolution of the human race are rapidly being eroded from cities (Zhou & Rana, 2012). The global trend of urbanisation and declining urban natural spaces has sparked international interest in the 'urban health' field, which looks at the characteristics of the urban environment influencing human health (Galea & Vlahov, 2005). The result is a multi-disciplinary body of literature that identifies relationships between increased urban natural environments and decreased stress (van den Berg, Maas, Verheij, & Groenewegen, 2010), anxiety and depression disorders (Maas et al., 2009), physical activity (de Jong, Albin, Skärbäck, Grahn, & Björk, 2012), improved general health (Wheeler, White, Stahl-Timmins, & Depledge, 2012), increased mortality (Takano, Nakamura, & Watanabe, 2002) and improved mental health (Francis, Wood, Knuiman, & Giles-Corti, 2012) outcomes.

In this multi-level study, a novel methodology was created and associations between different measures of natural environments and the health outcomes of a sample of adults living in Wellington City, New Zealand were investigated. More specifically, the study investigated whether improved views and/or increased ease of access to natural environments could be associated with positive mental health outcomes and increased physical activity.

1.2 Rationale for thesis

How do natural environments promote good health? This section introduces the primary causal pathways through which natural environments are believed to enhance human health. ‘Green space’ and ‘blue space’ are two encompassing terms that are used to describe natural environments, particularly in urban settings. Urban green space can be defined as an “integrated area comprising natural, semi natural or artificial green land.” (Zhou & Rana, 2012, p. 174). Examples of urban green spaces include parks, gardens, school yards, sports fields, protected spaces (e.g. riparian zones) or recreational forests (Cicea & Pîrlogea, 2011). Blue space pertains to natural dynamic or static water bodies i.e. rivers, lakes and oceans. Both blue and green spaces have been noted as places which create recreational opportunities, promote physical activities, enhance social ties and offer a place of aesthetic and natural beauty, ideal for mental and physical recuperation (De Ridder et al., 2004; White et al., 2010). While this study holds a focus on environments that play a therapeutic role specifically within built-up settings, it also incorporates nearby rural environments that may have visual significance to urban residents.

1.3 Causal pathways to improved mental health

Causal pathways refer to the processes through which an outcome is brought into being, in this case, how natural environments influence health within a population. Nutsford, Pearson, & Kingham (2013) identify three primary causal pathways which directly and indirectly may have a positive influence on mental health.

1.3.1 Salutogenic effect

The concept of ‘therapeutic landscapes’ is a well-established term (Rose, 2012) and can be described as places where the “physical and built environments, social conditions, and human perceptions combine to produce an atmosphere which is conducive to healing.” (Masuda & Crabtree, 2010, p. 657) In 1979, Aaron Antonovsky coined the termed ‘salutogenesis‘ to describe an approach focusing on factors that support and foster human health and well-being rather than on factors that cause disease. Using Antonovsky’s approach to health-nurturing places, numerous studies recognize blue and green spaces as ‘salutogenic environments’ a term synonymous with therapeutic landscapes, or as places that enhance and promote human health and well-being to some degree (Nutsford et al., 2013; White, Alcock, Wheeler, & Depledge, 2013a). In this way natural environments can be thought of as having a 'background' effect that is beneficial to human health. Ulrich et al. (1991) identified three theoretical perspectives in which natural environments may improve mental health through this effect. These theoretical perspectives (identified beloe) are likely to interweave and converge in a way that makes particular environments attractive due to their restorative properties (Ulrich et al., 1991). As this study pertains to an urban setting, the focus is on environments that play a therapeutic role within a built-up context.

Firstly*, Arousal theories* suggest that recuperation from stress is inhibited by mentally arousing characteristics such as movement, noise, complexity and intensity, all of which are common in urban environments (Ulrich et al., 1991). Similarly, the term '*overload'* can be used to describe urban environments that are mentally taxing and demand mental focus, thereby by inhibiting the brains ability to relax. In contrast, natural environments can offer a haven for relaxation in the absence of high energy, fast-paced and sensory-demanding characteristics (Ulrich et al., 1991). Secondly, e*volutionary* perspectives suggest that humans have a fundamentally intrinsic connection with natural environments due to humans evolutionary upbringing and the significant role they had in providing necessary resources for human development (Heerwagen & Orians, 1986; Ulrich et al., 1991). This view is reinforced by the biophilla hypothesis which states that there is a "genetic imperative to prefer natural environments"(Newell, 1997, p. 497). In 1983 Joachim Wohlwill posited the idea that the human brain processes natural environments more efficiently than an urban environment due to their evolutionary background. This ties in with the overload perspective mentioned above which suggests, urban settings promote stress due to an increased demand on directional brain processing in contrast to nature. Finally, there is a *cultural* upbringing in western society that leads to an association of relaxation with natural environments as a result of holidaying and other recreational activities (Ulrich et al., 1991). This influence is likely to be particularly strong in New Zealand where there is a strong culture for 'outdoor holidaying' (Cloke & Perkins, 1998).

1.3.2 Social interaction

Studies show that many psychological benefits can be gained through increased social interaction and intra-neighbourhood connectedness (Kweon, Sullivan, & Wiley, 1998; Miles, Coutts, & Mohamadi, 2012; Sugiyama, Leslie, Giles-Corti, & Owen, 2008). Natural environments, particularly green spaces, promote social interaction by providing a location for active engagement with other members of the community, whether it be planned or coincidental, both of which have been shown to be conducive for improving mental health (Sugiyama et al., 2008) and reducing psychological stress (Kweon et al., 1998). Increased social connection is recognised to be particularly beneficial for the health of elderly where decreased levels of mortality, reduced suicide rates, lower fear of crime and better physical health is associated with cohesive communities (Kweon et al., 1998; Zhou & Rana, 2012). Restricted mobility amongst the elderly also increases the importance of local neighbourhood connectedness as they are limited to less-physically demanding modes of transport and forms of social interaction. Kweon et al. (1998) & Sugiyama et al. (2008) note that public spaces provide an environment that promote and enhance social ties. The 'greeness' of public spaces has a strong influnce on the preference for an area while areas with larger numbers of trees had a higher number of people visiting, increased visit times and facillitated social interaciton. In a concluding statement Kweon et al. (1998) suggest that "modest improvements in [elderly] pyschological well-being may be achieved through creating a neighbourhood setting that supports the formulation of social and community ties" (p. 24) This was realised through greening efforts which were found to promote social interaction and neighbourhood coherence, particularly amongst the elderly.

1.3.3 Physical exercise

Natural environments, particularly useable green spaces, provide the opportunity for physical activity which is recognised to provide a multitude of positive effects on physical and mental health (Barton & Pretty, 2010; Pretty, Peacock, Sellens, & Griffin, 2005). Increased physical exercise affects mental health including, stress reduction, improved self-perception, and sleep and mood improvements, all which have been extensively explored (Paluska & Schwenk, 2000; Pretty et al., 2005; Thompson Coon et al., 2011). Natural environments, particularly green spaces are also credited with modifying urban settings in a way that makes a city more encouraging and conducive to physical exercise. Vegetation cleanses the atmosphere through removing dust particles and undergoing bacteriological purification by destroying microorganisms. It modifies the urban climate and mitigates urban heat island affect through providing shade and influencing humidity changes. It reduces noise, and finally, encourages the preservation and perpetuation of indigenous natural vegetation (Cicea & Pîrlogea, 2011). Through physical activity, natural environments are thought to improve mental health by encouraging activity and providing a pleasant environment for exercise to take place. While some studies find that residents living nearby to green spaces are more likely to be active (Björk et al., 2008; Coombes, Jones, & Hillsdon, 2010; de Jong et al., 2012), others have found no association (Maas, Verheij, Spreeuwenberg, & Groenewegen, 2008; Witten, Hiscock, Pearce, & Blakely, 2008). There is therefore on-going contention as to whether physical activity is a causal pathway or mechanism through which natural environments may improve metal health.

1.4 Health issues in New Zealand and beyond

Mental health disorders affect most people at some point throughout their life, while 16% of the general population experience a health disorder at any one time globally (Barton & Pretty, 2010). Specifically in New Zealand, 20% of residents were affected by some form of mental disorder in a 12-month period (Mental Health Commission, 2012). Mental illness is a major contribution to the health burden, as anxiety and depression are often precursors for other chronic conditions such as asthma, arthritis, diabetes, strokes and heart disease (Pretty et al., 2005). The World Health Organization (WHO) predicts that by 2020 depression and sequelae will be the leading cause of global poor health and have the biggest contribution to the disease burden (WHO, 2001). In New Zealand, psychological distress, a proxy for mental illness increased from 13% in 2006/7 to 16% in 2011 and is expected to continue increasing.

Physical health issues also have a significant effect on global mortality. The WHO reports that nearly two million deaths globally are caused by physical inactivity annually (Hillsdon, Panter, Foster, & Jones, 2006). Obesity prevalence was 28% in New Zealand in 2011/12, an increase from 19% in 1997 (Ministry of Health, 2012a). The Ministry of Health (MOH) recognizes this increasing trend as a challenge for future health management and expects an increase in type II diabetes and other obesity related conditions in the future (Ministry of Health, 2012a).

1.5 Significance of thesis

Mental and physical health problems significantly contribute to the health burden at both a national and global scale and are primary precursors for other chronic disorders. Through informed policy management and urban design this health burden can potentially be reduced, however more accurate New Zealand based studies are required. While numerous studies have found evidence to suggest the presence of natural environments in urban settings has positive influences on health, some contention remains (Lee & Maheswaran, 2011; Nardo, Saulle, & Torre, 2010). As mentioned above, this study contributed to the existing body of literature in a number of ways. It investigates the potential influence of both blue and green space features independently on health outcomes. The vast majority of research focuses on green space while blue space is waived or treated as a component of green space. Furthermore, this study introduced a novel measure as a quantification of visual exposure to natural environments. While visibility analysis of landscape environments is well established (Domingo-Santos, de Villarán, Rapp-Arrarás, & de Provens, 2011; Germino, Reiners, Blasko, McLeod, & Bastian, 2001; Wheatley & Gillings, 2000), it is yet to be used in health studies as an exposure variable. By creating visual exposure and access measures to natural environments, the findings of this study help untangle the causal pathways of natural environments influencing mental health. Furthermore it is a contribution to health geography as a discipline by further exploring the relationships between health and the geographic distribution of urban amenities. By understanding the links between the spatial distribution of natural environments and their influence on human mental health, better informed steps can be taken to reduce the prevalence of mental health conditions in urban populations.

1.6 Objectives and hypothesis

1.6.1 Objectives

The objectives of this study were to investigate whether there is an association between visibility and access to natural environments and mental health and physical activity in Wellington City, New Zealand, while controlling for individual and area level covariates. Specifically, the study aimed to:

i) Investigate whether increased visual exposure to green and blue spaces was associated with decreased psychological stress.
ii) Investigate whether increased access to green and blue spaces was associated with decreased psychological stress.
iii) Investigate whether increased access to green and blue spaces was associated with increased levels of physical activity.

iv) Investigate whether increased physical activity was positively associated with a decrease in psychological stress.

1.7 Thesis organization

This thesis is organised into seven chapters. 0 presented the topic and provided a general background covering the foundations on the importance and effects of natural environments in an urban setting. 0, the literature review, identified key studies and summarised findings while going into an in-depth review of the current understanding of the field and highlighted existing gaps and the potential value of further contributions to the field. Chapter 3 provided a theoretical base to natural environment exposure variables used, and in particular introduces the theory behind visibility analysis and its appropriateness for use in urban settings. Chapter 4 introduced the data sources and study design while the development of exposure variables and statistical methods were outlined in 0. 0 then re-visited each research statement mentioned above, presenting the findings. These were then critically discussed in 0 where an in-depth analysis of the findings takes place and any limitations or further improvements are discussed. Finally, 0 summarised the key findings, the implications of the research and validates the studies contribution to the natural environments and health field.

1.8 Review of chapter

Mental and physical health problems are of growing concern with increasing numbers suffering depression, anxiety and long-term health conditions. While many international studies offer strong support that natural environments are associated with positive health outcomes, there still remains contention, with some studies offering conflicting findings. Specifically, the causal mechanisms through which natural environments improve health are still not fully understood. By creating a novel visibility index this study was able to separate the visual pathway and investigate whether increased views of nature are associated with decreased psychological stress. It also contributed to the existing body of literature by further investigating relationships between increased access to natural environments and mental and physical health outcomes.

Chapter 2: Literature review

2.1 Current health climate

Despite better access to health related facilities in cities than in rural areas, city-dwellers have long been associated with worse health (Völker & Kistemann, 2013). A combination of sedentary and unhealthy lifestyles has resulted in a drastic economic increase on the national and global health burden. As such there are both health and economic driving forces that support the on-going research into the influence of natural environments on health outcomes. The WHO (WHO, 1948) defines health as “a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity”. While this study is an investigation into the influence of natural urban environments on mental and physical health, it is important to understand all three aspects of health due to their interconnected nature. For example Völker & Kistemann (2011) identify well-being as a complex and subjective state of consciousness influenced by a number of components. In section 2.1.1, mental health and the aspects of physical and social health that influence mental health are investigated.

2.1.1 Mental health

Stress and poor mental health are strong contributors to the disease health burden (Pretty et al., 2005), while mental health diseases such as anxiety and depression are often precursors for other chronic conditions such as asthma, arthritis, diabetes, strokes and heart disease. In turn, these are also associated with harmful behaviours such as smoking, and excess alcohol/food consumption, each with have their own associated health problems (Pretty et al., 2005). In light of this, the World Health Organization (WHO, 2001) predicts that depression and depression related illnesses (and their flow on effects) will become the leading cause of poor health by 2020 (Pretty et al., 2005).

Mental health disorders have an effect on most people at some point in their life, with 16% of the general population affected at any one time globally (Barton & Pretty, 2010). In New Zealand, 16% (approximately 500,000 people) have been diagnosed with a mental disorder at some point within their lifetime by a health professional. High levels of psychological stress affect 6% or 200,000 adults at any onetime (Ministry of Health, 2012a)

Prevalence of both health indicators are found to vary between groups. Females have higher rates of both psychological stress and diagnosed health conditions. Age is also found to have an influence on mental health. Younger women (aged 15-34) are the most likely to experience psychological distress while women aged 35-64 years have the highest rates of mental disorders (Ministry of Health, 2012a). Māori adults also have higher rates of psychological distress than other groups with Māori 1.7 times more likely to experience distress than non-Māori groups. In New Zealand, as with elsewhere in the world, a strong correlation exists between psychological distress and socio-economic deprivation (Pearson, Griffin, Davies, & Kingham, 2012). Rates of distressed individuals are more than three times higher in areas of high deprivation than areas with low deprivation (Ministry of Health, 2012a).

2.1.2 Physical health

Over the last 50 years there has been a rapid decline in physical activity in the majority of industrialised countries, particularly in North America and Europe (Pretty et al., 2005). Jobs demand less physical labour and a culture shift towards reduced activity levels is underway (Ellaway, Macintyre, & Bonnefoy, 2005). This combined with modern-day high calorie diets has led to an obesity 'epidemic' in some Western countries. Physical inactivity habits can be tracked from childhood and are known to contribute to a number of chronic diseases later in life (Barton & Pretty, 2010). Globally, physical inactivity is estimated to account for 6% of all deaths annually (van der Ploeg, Chey, Korda, Banks, & Bauman, 2012).

In New Zealand, obesity has increased from 9% (males) and 11% (females) in 1997 to 28% and 29% respectively in 2011(Ministry of Health, 2012a). Obesity is more pronounced in certain groups, with 44% of Māori adults obese (as defined by their BMI). Nearly one in three adults between 35 and 74 years of age are obese, with the highest prevalence among those aged 65-74 (38%) (Ministry of Health, 2012a). In 2006, 51% of New Zealanders 15 years and over met the physical activity guidelines of being active for 30 minutes or more 5 or more days a week (Ministry of Social Development, 2010). Males were found to exercise more than females with 54% compared to 47% reporting that they met the recommended activity guidelines respectively (Ministry of Social Development, 2010). Age was found to influence levels of activity with the most active group being people aged 35 years and younger and the least active group aged 65 years and older. Socio-economic deprivation was not found to be associated with levels of physical activity (Ministry of Social Development, 2010).

In a national sample, although 89% of adults in New Zealand reported 'good health', cardiovascular conditions are prevalent throughout the country (Ministry of Health, 2012a). Around 16% of adults take medication for high blood pressure, 10% take medication for high cholesterol, 5% have been diagnosed with ischemic heart disease and 2% have survived a stroke (Ministry of Health, 2012a). Diabetes has also been seen to increase over the last 15 years and now affects 5%, nearly 200,000 adults in New Zealand (Ministry of Health, 2012a).

2.1.3 Other determinants of mental health

Anxiety and fear of crime are also known to have a negative influence on well-being and can cause behaviour modification which may influence engagement within natural environments. Nearly half (40%) of New Zealanders indicated that fear of crime had a moderate to high impact on their quality of life. The 25-39 years age group was influenced the most by fear of crime while elderly were the least (Ministry of Social Development, 2010). Fear of crime was greater for woman than males across all age groups with 45% verse 34% reporting it had a moderately or stronger influence on the quality of life. Asians reported the highest fear of crime with 60% indicating it had a moderate or great effect on their quality of life. Māori reported 47% compared with Europeans at 36%. Finally, people living in area of high socio-economic deprivation were much more likely to report fear of crime than those living in affluent areas (49% verse 33%) (Ministry of Social Development, 2010).

Increased levels of social connectedness may be beneficial through providing a source of enjoyment and support or through allowing contribution to society. Social connectedness includes relationships between family, friends, colleagues, neighbours or members of fellow sports teams, volunteer groups etc. Numerous studies have found positive relationships between social connectedness and better health and wellbeing (Cornwell & Waite, 2009; Pearson et al., 2012; Zhou & Rana, 2012). Cornwell & Waite, (2009) found that individuals with a greater social connectedness, were generally healthier, happier and better off. Similarly, loneliness and neighbourhood isolation is a significant contributing factor to health conditions such as anxiety, stress or depression (Pearson et al., 2012). In 2008 16% of New Zealanders reported feeling lonely within the previous 12 months.

2.2 Natural environments and health

The notion that natural environments are beneficial for human health is not new. The first known record that supports this idea dates back to ancient Rome where residents noted a calming effect of vegetation in contrast to harsh anthropogenic noises generated by populated cities (R. S. Ulrich et al., 1991). However as alluded to in Chapter 1, it was not until the devouring of natural environments caused by urbanisation was truly realised that urban health and natural environments were recognised in academic circles. Early studies set out to explore the impact different landscapes had on psychological states and whether more 'natural' environments would promote stress recovery (Ulrich et al., 1991). These studies were predominantly qualitative, relying on verbal responses and self-reported emotional states and it wasn't until Ulrich (1981) first introduced a quantitative measure of psychophysiological states by monitoring brain electrical activity in the alpha frequency range. This research was backed up by a number of physiological measures indicating that natural scenes were influencing human moods. It wasn't until more recently however, that with the advent of process intensive spatial and statistical software packages that studies have begun to replace qualitative approaches of looking at the influence of natural environments of health outcomes with quantitative measures. Specifically, measures of access to natural environments at the neighbourhood level, which are objectively quantifiable, have become popular measures for assessing the effect of urban green spaces on a number of health outcomes (e.g. Nutsford et al., 2013; White et al., 2013a, 2013b). Recently studies have targeted causal mechanisms of natural environments and investigate whether they are a pathway leading to improved health (e.g. Maas et al., 2008; Nutsford et al., 2013). While these two types of studies are the primary focus of this literature review, it will also draw upon findings from related fields such as environmental preference studies, which seek to qualify which environments elicit positive emotional responses.

Pretty et al. (2005) identify three levels of engagement with nature. The first level is achieved simply by visually observing a natural environment. The second is being in close proximity to nature without actually participating in it, while the third is active involvement within a natural environment. While all three levels of interaction have been extensively studied in existing literature (e.g. Maas et al., 2009; Pretty et al., 2005; Ulrich et al., 1991), the majority of evidence pertains to either solely green space or simply treats blue space as green space. The study of blue space as an environmental variable influencing health remains an emerging subject with the majority of current research on blue space pertaining to the environmental ecology, microbiology and toxicology fields (Völker & Kistemann, 2011). As such there is little understanding on the independent affect it may have on human health. Numerous authors recognize this as a gap in existing literature and highlight the need for further research investigating the emotional and physical response to blue space (Völker & Kistemann, 2011; Wheeler et al., 2012). Nonetheless there is some evidence to show that independent blue space has an influence on human mental health and psychology. Below, the three levels of engagement with natural environments are explored while identifying key studies supporting each theoretical pathway.

2.2.1 Visual exposure to natural environments

The first level of interaction, or the influence between visual exposure to natural environments on mental health is well documented, particularly in the case of green space, and has been identified in a number of qualitative studies (Depledge, Stone, & Bird, 2011; Herzog, 1985; Rose, 2012; Velarde, Fry, & Tveit, 2007). Associations have been found between visual exposure to natural environments and stress reduction, improved mood, lower blood pressure, increase attention span, and stronger social ties (Velarde et al., 2007). The concept of environment preference (the recognition of particular environments being more desirable) has been explored in detail with blue and green space being internationally recognised as characteristics that create highly preferable environments (Pretty et al., 2005; Ulrich et al., 1991; White et al., 2010).

Hamilton & Morgan (2010) conducted a quantitative study that incorporated views of blue space into house valuation price models. They were able to augment previous hedonic models by incorporating measures of beach access and ocean visibility. While the paper explored associations between increased access and visibility of amenity values with an economic approach, results indicate a clear favouritism and willingness to pay for houses located closer to beaches and houses with ocean views. Another popular method used to assess the influence of views of nature on health outcomes is to assess the view from residential or workplace windows (R. Kaplan, 2001; Kearney, 2006). This research and the findings that different combinations of green and blue space interacting within the same environment are associated with different emotional responses provide the foundation for the use of visibility analysis as a quantifiable exposure variable in the context of health geography studies.

In 2005 (Putra & Yang, 2005) developed a GIS based 3D visibility analysis which generates volumetric indices of line of sight measures. It was designed in the hope that it would “map spatial and environmental perceptions of residential environment” (Putra & Yang, 2005, p. 26). While the novel approach introduces environmental visual perception and discusses its importance in health geography, the method has yet to be applied to a health geography question. Similarly Miller, Horne, Donnelly, & Morrice (2009) present a methodological paper that show the development of spatial analysis tools that seek to quantify the visual perception of natural environments for a case study in Edinburgh, UK. These studies highlight that the visual structures of residential environments are important, however to date there are no quantitative studies that directly assess the relationship between visual exposure to natural environments and mental health outcomes. The findings of environment preference studies identified above provide sufficient theoretical evidence to warrant the use of quantitative health geography methods to assess any associations between visual environments and mental health outcomes.

Moore (1981) observed that prisoners in an English prison with courtyard views had a 24% higher frequency of sick calls than prisoners with a view of farm land. Similarly, Kearney, (2006) observed that increased views of nature out of residential windows increased neighbourhood satisfaction which has been linked to improved mental health. In other research both home environments and work environments were found to benefit from views of open space with improved well-being, fewer illnesses, decrease in frustration and increased enthusiasm for work (Pretty et al., 2005).

The river Rhine in two German cities was found to have “therapeutic benefits” and was associated with a host of positive mood influences by Völker & Kistemann (2013). Laumann, Gärling, & Stormark (2003) found that their study subjects had increased levels of attentiveness when exposed to a simulated coastal environment as opposed to an urban setting. Ulrich (1981) was one of the few authors to identify whether the benefits of visual exposure to blue space was strongest in terms of associated health benefits. He found that while both green and blue had a positive influence on psycho-physiological state, the affect was stronger with visual exposure to water.

2.2.2 Access to natural environments and health

As mentioned above the second level of interaction identified by Pretty et al. (2005) relates to health benefits associated with being in close proximity to natural environments. This relationship has been extensively explored using GIS techniques which investigate the distribution and spatial relationships of natural urban features (Maas et al., 2009; Nutsford et al., 2013; Richardson, Pearce, Mitchell, Day, & Kingham, 2010; Stigsdotter et al., 2010; Wheeler et al., 2012; van den Berg et al., 2010). While general consensus finds increased access to natural environments associated with positive health outcomes, there remains some inconsistencies amongst existing literature (Lee & Maheswaran, 2011; Nardo et al., 2010). The use of proximity analysis as quantifiable measures is founded on the notion that nearby natural environments, particularly green spaces, are used more often. This notion is reinforced by findings from studies conducted in Denmark, England and New Zealand (Coombes et al., 2010; Nielsen & Hansen, 2007; Witten et al., 2008).

While general consensus finds that the amount of green space in a neighbourhood is associated with health outcomes, there remains some inconsistency amongst existing literature (Lee & Maheswaran, 2011; Nardo et al., 2010). In New Zealand, Richardson et al. (2010), found no association between access to green space and area-level cause-specific mortality and concluded that green space and any associations with health outcomes may vary between environments and social contexts. Lee & Maheswaran (2011) even went as far as to say that many studies were "limited by poor study design, failure to exclude confounding, bias or reverse causality and weak statistical associations" (p. 49). However, as more research is added to the expanding body of literature, evidence for positive influences of urban green space is mounting, with associations found between access to public green areas and perceived general health (de Jong et al., 2012), longevity (Takano et al., 2002), mental health (Barton & Pretty, 2010), and physical health (Pretty et al., 2005). More specifically, a study conducted in Auckland, New Zealand found that access measures of green space were associated with anxiety and mood disorder rates in neighbourhoods. The proportion of green space within 3km of small area centroids and network distance to useable green space were found to have a significant association with anxiety/mood disorders. Every 1% increase in the proportion of green space within 3km was associated with a 4% decrease in anxiety/mood disorder treatment rates. Similarly, a 100 metre decrease in distance to nearest useable green space was associated with a 3% decrease in rates of anxiety/mood disorder treatment (Nutsford et al., 2013). A study conducted in the Netherlands by Maas et al. (2009) found 15 of 24 disease clusters, including anxiety disorder and depression to be decreased for individuals living in areas with more green space within 1km. Stigsdotter et al. (2010) identified the affect distance to green space had on self-reported mental health in Denmark, noting that people living beyond 1km from green space were 1.42 times more likely to be experiencing stress than people living within 300m of green space.

While the vast majority of research pertains to green space, studies that focus on the independent effect of proximity to blue space on health outcomes are beginning to emerge. In a cross-sectional study, Wheeler et al., (2012) found that throughout England, there was evidence that self-reported ‘good ‘mental health was more prevalent amongst communities where access to the ocean was greater. White et al., (2013a) built upon this work by examining longitudinal data on self-reported heath from individuals. Individuals reported better general health and lower mental distress in the years that they were living within 5 km of the coast. Interestingly, stronger associations between living near the coast and reductions in negative health outcomes, were observed over increases in positive outcomes such as feelings of well-being when controlling for individual and regional covariates (White et al., 2013a).

As yet no published work has investigated the independent role of access to blue spaces on health outcomes in New Zealand, yet as noted by Richardson et al. (2010) approximately 65% of the population lies within 5km of the sea and blue space may have a greater effect in New Zealand than other study areas.

2.2.3 Physical activity in natural environments

The third level of engagement with natural spaces is active participation within the environment. The majority of existing studies group the 2nd and 3rd level of engagement together by inferring people who live near green spaces are more likely to be physically active within them. This also ties into the first level of engagement as there is a strong visual component involved when active within natural environments.

Pretty et al. (2005) conduct a study that evaluated the short term benefits of physical exercise in nature. After light physical exercise for 20 minutes there were significant psychological changes amongst the subjects. There was an increase in self-esteem and vigour and a decrease in confusion and tension. When analysed by group, only individuals who had exercised in a pleasing green environments had significant reductions in blood pressure for all three measurements indicating the surrounding environment does have an effect on psychological responses. Pretty et al. (2005) also noted that unpleasant green and urban scenes had a depressive effect on self-esteem. Sugiyama et al. (2008) provide empirical support that recreational walking plays a mediatory role in the positive association between green space and physical health. Interestingly, recreational walking in any setting does not explain the associated benefits for mental health and Sugiyama et al. (2008) make the suggestion that social interaction and green serenity found in green spaces are contributing factors.

Bauman, Smith, Stoker, Bellew, & Booth (1999) found that individuals living within coastal postcodes were 23% less likely to lead sedentary lifestyles, 27% more likely to report moderate levels of physical activity and 38% more likely to report high levels of physical activity once adjusted for major demographic factors. However due to the cross-sectional nature of the study they were unable to disprove that coastal environments are preferred by active people and a recommendation is made for future exploration. Ashbullby, Pahl, Webley, & White (2013) conducted a study that explored families' experience of participating in beach environments using qualitative methods. Physical activity was found to be a direct outcome of accessing beach environments, particularly amongst children. The study found evidence to suggest that promoting family leisure time at the beach could have positive influences on physical health and psychological well-being. In New Zealand, increased access to beaches was found to have a weakly significant association with physical activity (Witten et al., 2008) when controlling for potential confounders.

2.3 Contribution of this thesis

In existing literature, only green space has been extensively explored in detail and a valued contribution of this study is to include independent measures of both green and blue space which allows a cross-examination of mental health benefits of natural environments. While contributing to the expanding body of international literature, it was also the first study to investigate health benefits associated with blue space in New Zealand. Studies rarely combine measures of both green and blue space together providing the opportunity for this work to offer a valuable insight into the relative significance of the two separate natural environments in terms of their benefits on mental health. Furthermore this study was the first of its kind to quantitatively assess whether visual exposure to natural environments influences mental health and will build upon the qualitative studies that suggest views of nature positively influence health. Through this novel methodology the study extends the work conducted by Nutsford et al. (2013) by making a clear distinction between the access and visual causal pathways leading to improved mental health.

While a number of studies have been conducted within New Zealand that look at green space and health (Nutsford et al., 2013; Richardson et al., 2010; Richardson, Pearce, Mitchell, & Kingham, 2013; Witten et al., 2008), there remains gaps that need to be further explored. Specifically, the influence of blue space and the visibility of natural environments on health are yet to be investigated in a New Zealand context.

2.4 Review of chapter

In New Zealand, as with elsewhere in the world, an increasing economic demand on the health burden has seen an increase in studies investigating links between improved health and natural environments. While the majority of existing studies focus on the benefits of urban green space, health benefits of blue space are becoming more established. However there remains gaps in the literature that are yet to be explored. Specifically, the benefits of visible natural environments are yet to be examined using a quantitative measure. To date, all studies that investigate benefits of visualising natural environments take a qualitative approach which stand to subjectivity and bias limitations. Furthermore, in New Zealand the influence of blue space has yet to be associated with a mental health outcome. This study closed these gaps by introducing a new quantitative measure of natural environment visibility as well as incorporating tried and tested methods of access, in a New Zealand city.

Chapter 3: Exposure variables: a methodology review

Alternative methods for developing measures of access and visibility of green and blue space have the potential to significantly influence the associations found between natural environments and mental health and physical activity (Higgs, Fry, & Langford, 2012). This chapter reviews the techniques used to generate measures of exposure to natural environments and highlights the limitations and benefits of each.

3.1 Visual exposure measures

The use of Geographical Information Systems (GIS) for visibility analysis has grown rapidly in recent decades as a method for describing landscapes (Bartie, Reitsma, Kingham, & Mills, 2011) and its application is now commonly found in the landscape architecture, urbanism, geography and archaeological fields (Kim, Rana, & Wise, 2004; Llobera, 2003). With vast increases in data capture and quality, visibility analysis is beginning to shift from the traditional analysis of large open areas and focus more on detailed analysis within urban environments (Bartie et al., 2011).

Rural (or landscape visibility analysis), generally pertains to large-scale visibility analysis over natural terrain and is a broad indicator of environmental visibility. Comparatively, urban visibility analysis accounts for made-made structures and the complex nature of the built up environment as well as terrain, by incorporating high quality elevation data (Bartie et al., 2011). For this reason, and the process intense nature of visibility analysis, urban visibility tends to be conducted at a much smaller scale than rural visibility analysis. While this study focuses on natural environments within the urban environment, the influence of visible natural environments extends beyond the city limits. It will, therefore, examine methods commonly used in both these fields. It will also identify major limitations of visibility analysis and the different techniques for mitigating these.

3.1.1 Existing visibility models

Isovist visibility analysis was the traditional approach taken to describe urban environments. Developed by Benedikt, (1979), the isovist analysis is a simple representation of two dimensional visibility from a given vantage point. Generally, terrain is not included and the focus is on man-made structures that impede visibility. In the urban isovist, the built environment is generally represented by architectural plans which designate building foot prints and location. Building heights are not included. In essence, an urban isovist is simple representation of visible space, influenced by the spatial location of physical structures represented as polygon features.

Viewsheds are built on the principles of the isovist visibility analysis with the added benefit of incorporating underlying terrain. Initially they were primarily used for rural visibility analysis. The purpose of the viewshed tool was to classify a landscape into visible or non-visible areas from a single or multiple observer points. It achieves this by generating lines of sight (LoS) between an observer point and any individual cell of a gridded elevation surface or Digital Elevation Model (DEM). Every cell is initially treated as visible, unless the LoS detects intervening topography or other obstruction. In its most basic form, this is the basis of the ‘binary viewshed’ which produces a raster surface indicating visibility by ‘1’ and non-visibility by ‘0’ (Wheatley & Gillings, 2000) (see Figure 1). While viewsheds were traditionally applied exclusively to large scale rural analysis, the advancement of high quality data has broadened the scope of viewshed visibility analysis by enabling the same methodological principles to be applied to urban environments. In light of this, modern viewsheds now surpass isovist analysis due to their ability to conduct visibility measures across complex terrain and incorporate man-made structures. This has led to viewsheds becoming much more popular visibility analysis methods in almost all fields beyond landscape architecture (Bartie et al., 2011; Palmer & Shan, 2000).

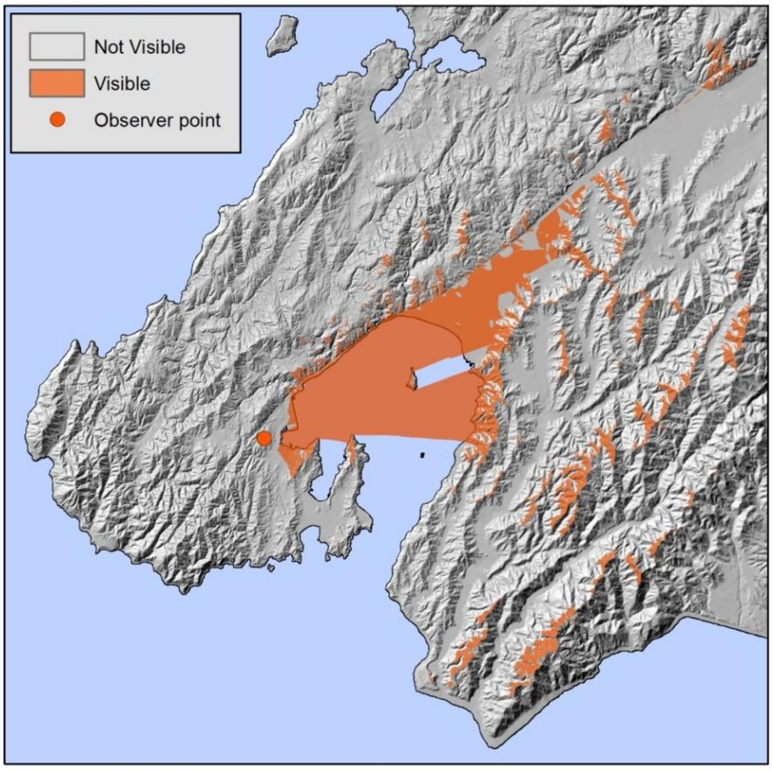


Figure 1: Binary viewshed output created with the ESRI ArcGIS spatial analyst viewshed tool from one observer point.

3.1.2 Limitations of visibility analysis

While visibility analysis is widely recognised as a practical GIS tool, its numerous limitations are well documented. Pragmatic issues involve aspects of visibility (specifically from a human perspective) and are not concerned with the analytical techniques but are limitations inherent within the field of visibility itself, not the digital representation of it. These limitations are equally applicable to both GIS studies and non-GIS studies (Wheatley & Gillings, 2000). In visibility analysis there is a tendency to treat everything *theoretically* visible as visible in reality, however there are several factors which undermine this assumption. Firstly, twenty-twenty vision is assumed and as such there is no accounting for visual impairment between individuals (Wheatley & Gillings, 2000). Object-background clarity is a term used to describe how well an object stands out against its surroundings. An object may be theoretically visible but completely indistinguishable if it is blending into its environment (Wheatley & Gillings, 2000). Temporal and cyclical variations are often ignored in visual analysis; however numerous cycles interplay with one another and it is worth noting the impact they have. The diurnal cycle has the most profound effect on visibility with the visual capacity nearing zero during night hours. Dusk and dawn are also associated with properties influencing vision such as low sun and morning haze. Seasonal and climatic cycles are also capable of altering visibility conditions, both unexpectedly (i.e. storm events) and predictably (i.e. seasonal variations). Temporal variations in tree foliage which occur with seasonal changes, especially in deciduous trees are the most noted impact of seasons on both urban and rural environments (Wheatley & Gillings, 2000).

Perhaps the most well established criticism is the impact of intervening vegetation (Bartie et al., 2011; Kumsap, Borne, & Moss, 2005; Llobera, 2007; Murgoitio, Shrestha, Glenn, & Spaete, 2013; Wheatley & Gillings, 2000). With the advent of Light and Detection Ranging Data (LiDAR), a technology that captures the back-scatter of pulses of light radiation reflected of the earth's surface using an aircraft, highly accurate representations of terrain and surface features such as vegetation can be captured. While this data acquisition method is becoming increasingly popular it is still expensive and unpractical to use over large scale areas. Therefore in the GIS, vegetation, namely trees, are typically represented as solid protrusions that block LoS analysis. However, in reality visibility exists both beneath the branches and to some extent, through the foliage. Tree height, width and foliage cover also vary, meaning generalisation is a necessary constraint (Wheatley & Gillings, 2000). While the vast majority of viewshed analyses make no attempt to account for vegetation and rather choose to recognize it as a method limitation, there have been numerous adaptive techniques to mitigate the influence of intervening vegetation, each with varying degrees of effectiveness.

3.1.3 Mitigation of recognised limitations

The limitations of viewshed analysis are well established and a number of adaptions have been developed that improve their accuracy. The prominence of a visual target is greatly affected by its distance from an observer and a major shortcoming of standard viewshed analysis is its failure to weight visible cells based on their distance from an observer point. Distance decay functions introduce a method to mitigate this issue by quantifying the visibility of environments in a way that reflects the decline in size and clarity of visible objects with increasing distance from the observer. The most common distance decay function, and best suited in the context of vegetation analysis is the exponential distance decay (Kumsap et al., 2005), which states the significance of visible areas increases exponentially the closer it is to the observer. The Higuchi Viewshed, was a method developed to reflect the importance of distance in visibility models by developing a standardised index (Wheatley & Gillings, 2000). Three visibility categories were defined as short-distance view (foreground); middle-distance view (mid-ground) and long-distance view (background). Using trees as a demonstrative object common to natural landscapes, Higuchi defined short-distances as the area where tree leaves could be seen to flutter and wind could be heard rustling the leaves, or alternatively, 60 times the size of the most dominant tree species in the area (Wheatley & Gillings, 2000). The middle-distance visibility zone comprised of trees that had visible tree tops but the individual tree was indistinguishable. In this zone the feature of interest begins to interplay with its environment and other impacts such as haze and mist interplay with the visual scene. The background zone begins at 1,100 times the size of a standard tree. At this distance only forests are distinguishable and colour is detected as shades of lighter or darker patches.

The process of creating a Higuchi Viewshed is straightforward and categorizes visible areas into the three zones defined above; foreground, mid-ground view and background view. Summary statistics for visible areas can then be calculated within each distance band and the visual scene from an observers perspective can then be somewhat conceived by the amount of visual area within each distance band. Is an observers view dominated by natural environments within the short-range or can they only see green space in the long-range view? Wheatley & Gillings, (2000, p 19) define the relationship as below:

> "*Features which are in the short-distance range can be thought of as integral and immediate to the everyday lives of the occupants of the viewpoint. In contrast, features in the middle- distance form what we might think of as the scenic landscape setting for a given viewpoint, replete with spatial and temporal depth and acting as both referent and context of meaning for a given locale. Features in the long-distance category are those which may be visible but are not readily identifiable, having lost any distinctive and individual identity*."

Many GIS software packages include parameters within the viewshed tool that are influenced by distance. For example, ESRI's ArcGIS 10.2 viewshed (Redlands, CA) analysis tool can be modified to adjust for atmospheric correction and the Earths curvature when conducting LoS analysis, both of which become particularly important in visibility analysis over long distances. The algorithm compensates for atmospheric refraction which forces light to bend as it propagates throughout the atmosphere. The severity of this refraction is influenced by variations in air pressure, humidity, temperature, and elevation. The default settings for these parameters were used which are designed to simulate visibility at mid-day under clear conditions.

The absence of vegetation in visibility analysis is one of the well-documented limitations in landscape visibility. A number of methodologies have been developed to mitigate this issue each, with varying degrees of success. The simplest and most common method is to create a vegetation raster layer by extruding land areas by the average height of the dominant species and merge it with the terrain surface model. Flaws are inherent with this method, the most noteworthy being the assumption of constant tree height. It also treats vegetation as impenetrable barriers whereas vegetation is known to be variably and partially transparent. With improvements in surface elevation data capture however, a number of techniques that investigate partial visibility through vegetation have emerged (Bartie et al., 2011). Work by Llobera (2007) employed Beer–Lambert's attenuation law, which proves light through a medium decays at an exponential rate. While Llobera's work was met with success, it was only suited for rural environments dominated by one species and is less effective in urban environments where vegetation may be sparse and of varying type. Other techniques were developed in the United States which treated vegetation as a layer hovering above the terrain, allowing for LoS analysis to pass beneath the vegetation canopy (Bartie et al., 2011). Another method was to convert individual trees collected as point data into cones. Cone height and width could be based on attribute information tied to the tree points (Bartie et al., 2011).

3.1.4 Specific considerations for urban environments

While urban environments are an integral consideration in isovist visibility analysis they were traditionally rarely included in viewshed analysis. The reasons for this are twofold. Firstly, in the context of rural landscape visibility (for which viewsheds were traditionally used) buildings and other human-built surface features are likely to be too few and too spaced out to warrant inclusion or to exert a noteworthy impact on visibility. The second reason lies in data quality. Until relatively recently, DEM rasters were of such a course resolution that it was difficult to incorporate individual buildings with a suitable degree of accuracy. It is also difficult to obtain spatial data for building structures that are accurate in both their locations (X,Y) and heights (Z) (Sander & Manson, 2007). Still, there are a number of techniques that aim to include urban surface structures into visibility analysis and these are becoming common-place following the deliverance of high quality data.

Map algebra, the process of combining two raster surfaces together, is often used to add extruded building footprints into terrain models. This allows for visibility analysis to be conducted within cities, where vertical surface features create a stark contrast to other terrains. For example VanHorn & Mosurinjohn (2010) added extruded building footprints into a DEM when assessing sniper threat in Grand Rapids, Michigan, USA. Likewise Pearson, Nutsford, & Thomson, (forthcoming) conducted a similar approach to assess smoking visibility in the downtown area of Wellington, New Zealand. LiDAR point data, which can be accurate to less than 15cm (VanHorn & Mosurinjohn, 2010), in combination with increasing computational power has extended the scope of visibility modelling applications (Llobera, 2003). This bypasses the need to combine building footprints with terrain data as the man-made structures and terrain can be captured simultaneously with LiDAR data.

3.1.5 Visualscapes – From 2D visibility to 3D visibility

The vast majority of visibility analysis is conducted in either the 2nd dimension such as isovists or in the 2.5 dimension with viewsheds. While these methods are without a doubt useful, especially in large scale terrain analysis, they use a “Gods eye view” approach and fail to portray the vertical dimension. In other words, the viewshed’s major shortcoming is that it fails to accurately represent the view from a human perspective. A realization of this limitation sparked a new generation of visibility analysis which moves away from 2.5 dimensional viewsheds and express visibility within a 3D sphere. These methods have been termed viewscapes.

In the last two decades a number of different viewscape methodologies have been introduced. Llobera (2003) conducted a review of existing visibility analysis methods and noted that isovists, along with viewsheds, represent only a small proportion of the possible ways to quantify an environment’s visibility structure. He introduced a number of terms that could expand upon existing measures of visibility such as 'visual impact' and 'visual prominence' and investigated the potential use of a vector field to represent visual exposure. Domingo-Santos et al., (2011) developed a GIS visibility tool that yielded higher precision values than existing viewsheds by calculating the 'solid angle' of each visible cell within a DEM. Solid angles are described as the "surface area covered by a given object on the retina of the observer" (Domingo-Santos et al., 2011 p. 57) Solid angles take into account every visible cells relative aspect, relative elevation, slope and distance from observer, all which influence the visual structure of an environment. The work by Domingo-Santos et al. (2011) represents a shift in focus from 'environment visibility' to 'visibility of the environment' *from an observer's perspective*. It can be argued that this focus shift makes visibility analysis more meaningful in urban health contexts where the visual structure from a human subject's perspective is paramount due to the vertical nature of urban features.

3.2 **Access exposure measures**

With the emergence of GIS technology, measures of accessibility are now able to be much more precise than traditional methods such as Euclidean distance (Thornton, Pearce, & Kavanagh, 2011) or area of green space within an administrative boundary (Richardson et al., 2010, 2013). Improved measures of access to natural environments, particularly to green space, are well documented and include proximal access through a road network (Nutsford et al., 2013) or the proportion of green space within defined buffers (Maas et al., 2009). Higgs et al. (2012) investigated the implications of using different GIS-based techniques for measuring accessibility to green space and warned that inappropriate methods may directly influence results and limit generalizability.

3.2.1 Proximity to natural environments

Higgs et al. (2012) identify three factors that were found to vary throughout existing methodologies for creating proximity measures. Measures of proximity are made between two points, however these can be difficult to accurately represent in a GIS. In ideal scenarios, where individual level health data is available, proximity measures are made from the residential address of each individual to the nearest green space feature (either perimeter, centroid or access point). However, in order to preserve confidentiality and not breach ethical laws, health data is generally only available at an area-level, such as by neighbourhoods. Access measures must therefore be summarised from a single point within an area or polygon. This may be the area centroid, however the population weighted centroid is identified as best practice by Higgs et al. (2012). Secondly, representation of natural environments in the GIS varies between studies. A park (for example) may be represented by a centroid point, a number of access points representing park entrances, or a polygon defining the park perimeter. While calculating distance to park entrances is most ideal (Higgs et al., 2012), there is a trade-off between data collection cost, data process time and precision. Finally, the method used to describe proximal access varies. Access is generally calculated as the linear or Euclidean distance to a feature (Wheeler et al., 2012; White et al, 2013a) or as distance through a road network (Miller et al., 2009; Nutsford et al., 2013). The latter is thought of as a more accurate measure as it encapsulates a more realistic travel time of accessing the nearest natural environment (Higgs et al., 2012). These three factors all impact the validity of access measurements and should all considered before conducting proximity analysis.

3.2.2 Access to quantity of natural environments

An alternate method of measuring access to natural environments is to calculate the amount that falls within a defined distance of an origin point (Maas et al., 2009, 2006; Nutsford et al., 2013; van den Berg et al., 2010). This method is popular because different distance buffers represent the influence of natural environments at different spatial extents. A smaller buffer represents natural environments at the local neighbourhood level while larger buffers reflect the influence of natural environments within the greater neighbourhood or region and can be indicative of the background naturalness of a neighbourhood. Through this measure natural environments can either be expressed as the total area occupied or as a proportion of the total available area. The recommendation of Natural England, a Government agency is that all residents should have access to green space areas within 300m of their home (Coombes et al., 2010) which provides a minimum distance in which to create quantity buffers. A radius of 3km is often used as a upper limit for calculating access to quantity of green space (Maas et al., 2009, 2006; Nutsford et al., 2013; Vries, Verheij, Groenewegen, & Spreeuwenberg, 2003) as it reflects a 30 minute walking distance. This buffer includes natural environments which are likely to be visible and easily accessible as individuals move throughout their extended neighbourhood.

3.3 Review of chapter

While qualitative methods have long been employed in studies that investigate the health benefits of visually observing natural environments, the same relationship has not previously been tested using quantitative measures. In other fields, environment visibility is commonly measured using viewshed analyses, however this technique has a number of shortcomings which make it an inadequate tool for measuring visibility from the perspective of a human individual. As a relatively new development, 'viewscape' measures provide a more appropriate alternative as they incorporate measures of the visual significance of terrain. These viewscape measures are adapted for suitability in the context of visibility of natural environments and the methodolgies are described in Chapter 5.

Quantitative measures of access to natural environments are well established. Access is often defined as either the proximal distance to green or blue space or the proportion that falls within a Euclidean distance buffer. This study identified the strengths and limitations of different measures of access and these influenced the methodological design outlined in 0.

Chapter 4: Study design and data

4.1 Study region

This study was conducted in Wellington City, New Zealand's Capital, and a country that is internationally renowned for its 'clean and green natural environment' (Patterson & Mcdonald, 2004) (Figure 2). With roughly 18 000 km of coastline every point in New Zealand is within 130km of the coast. National parks, forest parks, land reserves and marine reserves cover 7 373 053 ha (Patterson & Mcdonald, 2004) and a clear prioritisation for the protection of natural environments is evident through the introduction of the Environmental Protection Authority in 2011. As New Zealand's 3rd largest city, Wellington was selected as the study region for a multitude of reasons. Firstly, as a coastal city, with an abundance of green spaces, there is a high degree of variation in measures of access and proximity to natural environments amongst the residents of Wellington. Wellington City is a heavily urbanised city, with the majority of the population living in close proximity to the coast. While the CBD is primarily near sea-level and relatively flat, it is bordered by hilly terrain. This varied terrain of Wellington made it a suitable region for this study as it provided the opportunity to thoroughly test the visibility techniques developed to quantify green and blue space visibility.

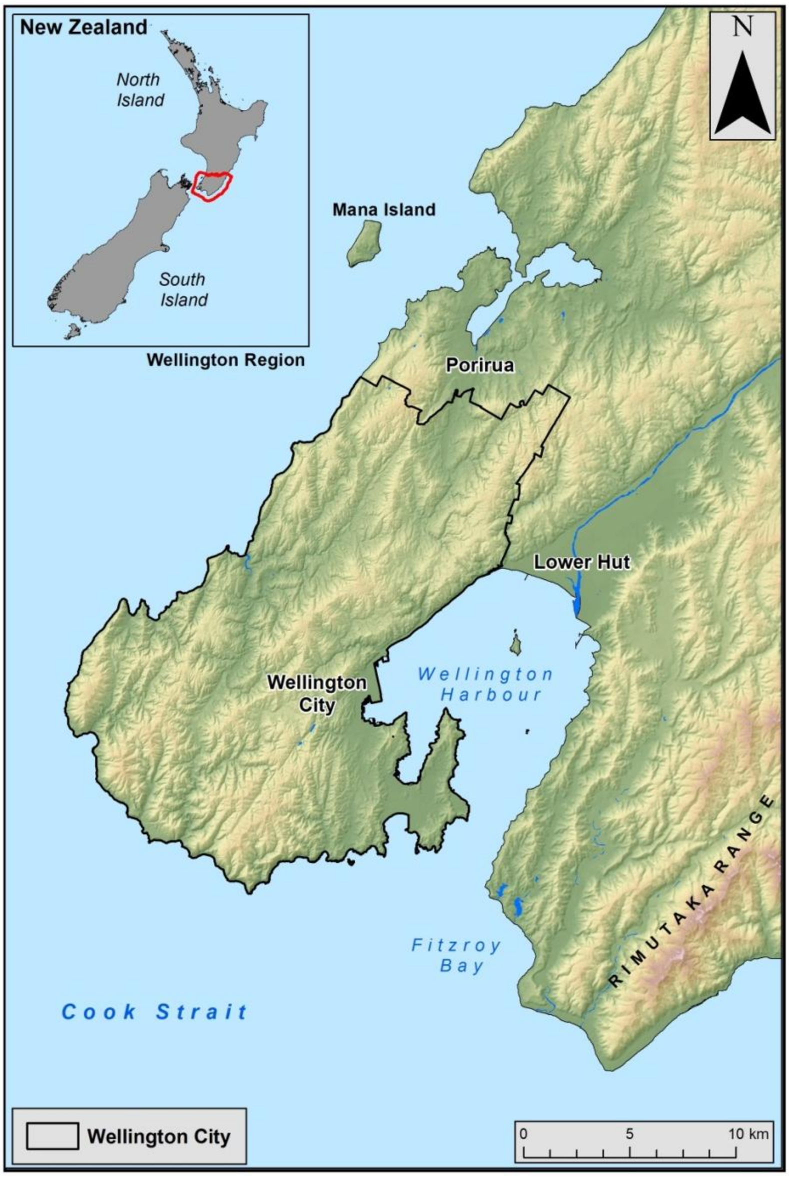


Figure 2: Map of the study region showing Wellington City and the greater Wellington Region.

4.1.1 Population demographics of Wellington

The wellington region has a resident population of 448 956, approximately 11% of the country's total population. In 2006, 179 466 people were living within Wellington City and lived in 68 901 dwellings (Statistics New Zealand, 2006).

New Zealand is an ethnically diverse nation with four major ethnic groups recognised in the 2006 census. New Zealand Europeans make up the largest ethnic group with just over 2 500 000 people or nearly 70% of the total population. The second largest is the indigenous Māori population who make up 15% of the population. The Asian ethnic group accounts for nearly 10% of the country's population and is the fastest growing ethnic group in the country. Pacific peoples account for 6.5% of the population with a highly youthful population (38% aged 0-14 years) (Ministry of Social Development, 2010).

The ethnic groups of the Wellington region somewhat reflect the nation average. Māori and Asian ethnic groups are slightly under represented at 12% and 8% respectively while European and Pacific peoples are slightly over represented at 77% and 8% respectively (Statistics New Zealand, 2006). There are recognised health disparities between the ethnic groups of New Zealand. Māori experienced the highest indicator mortality rates at all ages, followed by Pacific peoples, European and Asian ethnic groups (Ministry of Health, 2012a). Socioeconomic deprivation also varies through ethnic groups with Māori and Pacific peoples disproportionately represented in areas of high deprivation (24.1% and 35.7% respectively in the highest deprived decile vs. 4.5% NZ European) (P. White, Gunston, Salmond, Atkinson, & Crampton, 2008). Reasons for the unequal deprivation status of the indigenous Māori group stem from the colonial history of New Zealand, which in turn, influences health and social conditions of this group, contributing towards health disparities.

4.1.2 Natural environments in the Wellington Region

Throughout the study area of Wellington City (including a 15 km buffer to encapsulate natural visible natural environments beyond the city limit) there is a total of 2 076 km^2 of natural environments (see Figure 3 or Table 1a for a breakdown of natural environments by type). Wellington City is surrounded by coast on three sides with a total of 103 km of coastline. The Wellington City Council manages 2 500 ha of bush, 200 ha of general purpose grass including parks and verges, 100 ha of sports grounds and 98.5 km of tracks (Regional Public Health, 2010). See Table 1b for a breakdown of the green space into 'useable' and 'other' within Wellington City (i.e. not including the 15km buffer)

Table 1a: Break down of natural environments within the Wellington Region by area (Wellington City plus 15km buffer)

Natural environment categories	Area (km^2)	Proportion of total natural environments
Green space	795.66	38%
Blue space	1 279.87	62%
Total natural environments	2 075.53	100%

Table 1b: Break down of green space within Wellington City by area

Green space categories	Area (km^2)	Proportion of total green space (%)	Proportion of Wellington City land area (%)
Useable green space	22.26	10%	8%
Other green space	215.48	90%	74%
Total green space	237.75	100%	82%

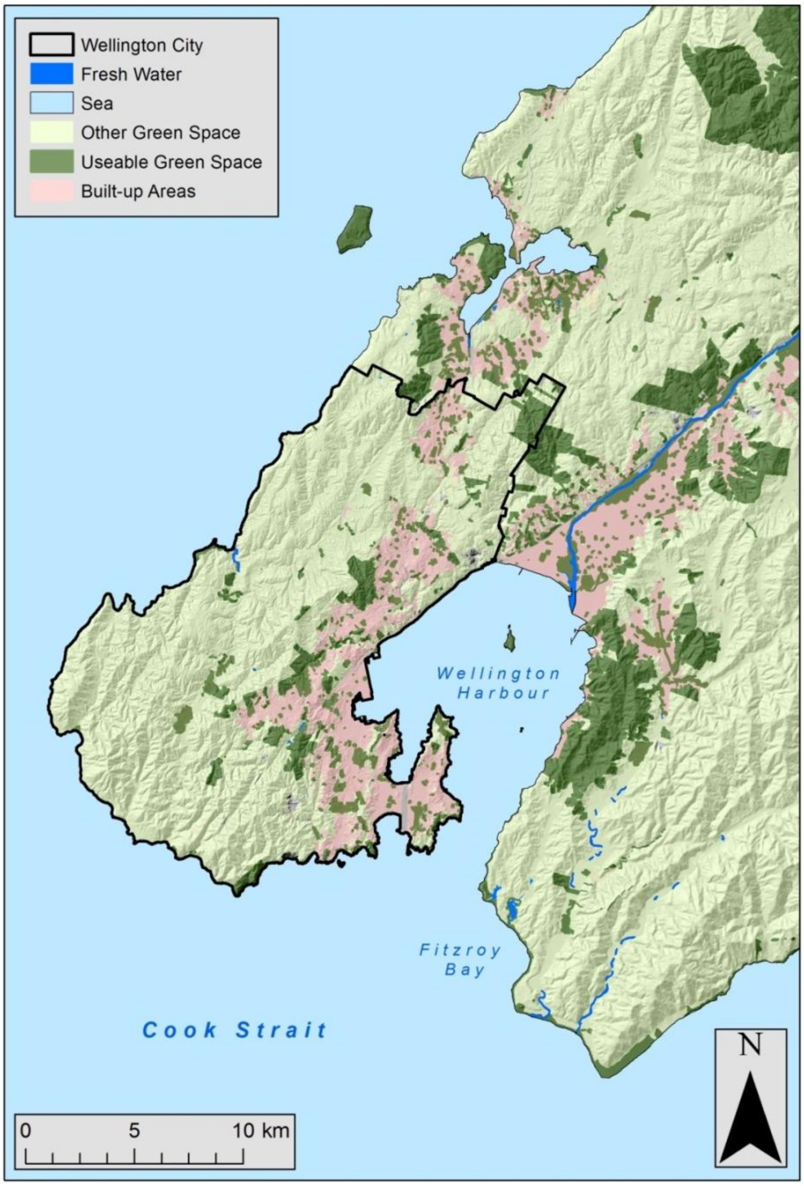


Figure 3: Green space (useable and other) and blue space within Wellington City, and the greater Wellington region.

4.2 Overview of methods and design

This multi-level study investigated whether personal indicators of psychological stress and levels of physical activity were associated with area-level exposures to natural environments while controlling for individual and area level covariates. A total of 33 exposure variables to natural environments which measured visibility, proximity and access to quantity were created using GIS spatial analysis techniques. Regression models were created with Stata statistical software (StataCorp, 2011), to assess whether these exposure variables were associated with health outcomes while controlling for covariates.

4.3 Area-level data

4.3.1 Natural environments data

Green spaces and oceanic blue spaces used in this study were a modified subset of a green space layer, developed by Liz Richardson and others (Richardson et al., 2010). The green space dataset was derived from three sources in 2008; the Land Class DataBase II, the Department of Conservation land register, and the Land Information New Zealand parcel database, each which had differing degrees of contiguous coverage, resolution and attribute information. The Land Cover Data Base was the largest dataset with nationwide coverage, however, it had the least attribute information associated with it and had the lowest spatial resolution of the three datasets. This was therefore used as the base data layer and updated with the more accurate, but less contiguous datasets from the Department of Conservation and Land Information New Zealand. This resulted in a contiguous spatial dataset representing green spaces and some blue space throughout New Zealand. While the green space dataset included oceanic blue spaces, it did not incorporate freshwater blue space features such as lakes and rivers. It was therefore appended with spatial data layers of wide river sections and lakes obtained from koordinates.com, New Zealand's official portal for geospatial data.

Both green space and blue space features were characterised as either 'useable' or 'not useable'. Useable spaces included urban parkland, beaches, and any non-commercial forestry areas that were accessible by the public road network. All other areas were classified as non-useable. Private gardens were excluded from the study and only green space areas larger than $500m^2$ were included, a modification on the original green space dataset which included areas smaller than $200m^2$ (Richardson et al., 2010).

Further classification was made to the natural environment data to provide a proxy of visual quality. Due to the subjective nature of quality assessment this classification was as kept as simplified as possible. Environments were classified as either 'High Quality', 'Average Quality' or 'Low Quality'. These classifications were made based upon the attribute information pertaining to each land parcel which included 12 categories ranging from indigenous forest to low producing grass. The final processed data layer therefore included attributes for each natural environment indicating the type of space (green space or blue space), the relative quality of the space (High, Average or Low) and whether the space was useable or non-useable. From this dataset, five raster datasets were created, each spatially representing one of the following natural environment categories:

1) All natural environments
2) Useable natural environments
3) All green space
4) Useable green space
5) Useable blue space (all blue spaces treated as useable*)

* *As non- useable blue space represented >1% of total blue space, no effort was made to distinguish between useable and non-useable blue space.*

4.3.2 Terrain models

Koordinates.com has three Digital Elevation Models publically available at different resolutions for the Wellington region. The largest resolution DEM freely available was provided by the University Of Otago National School Of Surveying (2011) at 15m resolution and covers the land area of New Zealand**.** The Wellington City Council provides two DEMs. The first was a 5m DEM available for the entire Wellington Region while the second, a 1m resolution DEM was restricted to the City limits. All three rasters were combined in order to take advantage of the higher resolution data where possible.

4.3.3 Building footprints data

Highly accurate building footprints within Wellington City, which included a height above sea level attribute, were provided by the Wellington City Council. Using ESRI ArcGIS 10.2 (Redlands, CA) these building footprints were converted into raster format. After pixel alignment adjustment against the base elevation raster was conducted, the two raster surfaces were merged to create one surface that reflected both natural landforms and buildings.

4.3.4 Vegetation height data

For visibility analysis purposes height information was assigned to vegetation and a generalised technique similar to the one followed by Tomko, Trautwein, & Purves (2009) was applied. A vegetation height attribute was assigned to the vegetation data layer which reflected the dominant species for each vegetation category. For example enclosed pine canopy and indigenous vegetation were assigned height values of 8 and 10 metres, respectively while low-producing grass was assigned 0.15m. These height values were then used to build a vegetation height raster layer which in turn was added to the terrain model. The resultant raster layer comprised of three elements; i) terrain elevation ii) building structures and iii) vegetation heights.

4.3.5 Road network data

Road network centrelines for New Zealand were provided by Critchlow, a geospatial consultancy firm, in 2009. Road segments had attribute information corresponding to length and travel times, allowing for travel distance calculations to be made between two points throughout the network.

4.3.6 Administrative boundaries data

Administrative boundaries including meshblocks, census area units and territorial authorities were provided by Statistics New Zealand in 2006. Meshblocks are New Zealand's smallest aggregation of census data, with approximately 100 residents each (Hay, Whigham, Kypri, & Langley, 2009). New Zealand is made up of 46 263 meshblocks (MBs) which aggregate to make larger census area units of which there are 1 927. The average population per area unit is 2 000 people and in urban areas approximately corresponds to one city block. Census area units can be further aggregated into 68 territorial authorities defined under the Local Government Act 2002 as a city or district council. The Wellington City territorial authority contains 1 815 MBs which can be aggregated into 68 area units.

4.3.7 Air pollution data

Particulate Matter below 10 micrometres (PM_{10}) is particle pollution, some of which is released directly in to the atmosphere from anthropogenic processes such as engine combustion (Kingham, Fisher, Hales, Wilson, & Bartie, 2008). Atmospheric PM_{10} is one standard measure of air pollution and there are many identified links between PM_{10} concentrations and physical health outcomes (Pope, 2000). This was considered to be a potential confounder between access to natural environments and physical health because greener environments tend to be less polluted due to an absence in anthropogenic pollution emitting sources (Richardson et al., 2010). PM_{10} concentrations were previously modelled for New Zealand using an atmospheric dispersion model which combined meteorological data with emissions data to approximate pollution levels (Kingham et al., 2008). Average PM_{10} levels (PM_{10} μgm^{-3}), were then extracted by area units. For use in this study, each meshblock was assigned the average PM_{10} concentration value of the census area surrounding it.

4.3.8 Crime data

Average annual crime rates were provided by census area unit by the New Zealand Police for 2008-2010, using NZ resident population as the denominator. Crime was controlled for as there is evidence to suggest increased local crime is associated with poorer mental and physical well-being in New Zealand (Pearson & Breetzke, 2013).

4.3.9 Population density data

Population density was calculated by dividing the total resident population for each MB by its area in km^2. Population density was adjusted for as a measure of urbanity as natural environments and mental health are expected to vary with the degree of urbanism (Richardson et al., 2010).

4.3.10 Area-level deprivation data

Deprivation is often a strong confounding factor in health research. The New Zealand Index of Deprivation (NZDep06) is an area-level measure of socio-economic deprivation that combines nine variables from the 2006 census including household income, employment, home and car ownership, and receivership of government assistance programs. Deciles of NZDep06 were used for each MB in the study area (1 = low, 10 = high) (Salmond, Crampton, & Atkinson, 2008)

4.4 Individual-level data

The New Zealand Health Survey (NZHS) is designed to capture health and individual level data for a representative sample of the usually resident population of New Zealand. The information collected by the survey covers population health, long-term conditions, health service utilisation and patient experience, health risk and protective factors, health status and socio-demographics (Ministry of Health, 2012b). It was first conducted in 1992/93 and has since been repeated four times, with the most recent survey in 2011/2012. An adult survey targeting residents 15 years and over and a child survey targeting residents aged from birth to 14 years are conducted simultaneously. The survey uses a multi-stage, stratified, probability-proportional-to-size (PPS) sampling design, which yields an annual sample size of approximately 13 000 adults and 4 500 children. For further details see the New Zealand Health Survey Methodology Report (Ministry of Health, 2012b). The areal sample is primarily based on MBs, and areas with Māori and Pacific peoples over-sampled.

This study utilised data from the 2011/2012. Throughout New Zealand 5 014 males and 7 356 females were interviewed, a total of 12 370 residents. They adult survey had a weighted response weight of 79% and a coverage weight of 54% (Ministry of Health, 2012b). In the study site of Wellington, 460 residents were surveyed and lived in 46 unique MBs. This section outlines the individual-level health variables obtained from the 2011/2012 NZHS.

4.4.1 Mental health

The Kessler Psychological Distress Scale (K10) was designed as a simple measure of psychological stress, designed for large sample population studies (Oakley Browne, Wells, Scott, & McGee, 2010). The K10 involves 10 questions about personal feelings over the previous month (See Appendix A for full list of questions) and has proven to be an accurate predictor of anxiety and mood disorders (Oakley Browne et al., 2010). Each question can be answered using a likert type scale (Oakley Browne et al., 2010) with values between 0-4 where 'all of the time' = 4; 'most of the time' = 3; 'some of the time' = 2; 'a little of the time' = 1; 'none of the time' = 0; while all other values were set to missing and scores are then summed. The 2001 Victorian Population Health survey determined thresholds for classification of distress which are now largely used (Kessler et al., 2003; Oakley Browne et al., 2010). Scores of 0–5 are labelled as 'none or low'; 6–11 as 'moderate'; 12–19 as 'high' and 20–40 as 'very high' in regards to the likelihood of having a mental health disorder. The K10 allows detection of small, but potentially significant shifts in the stress within populations which may not be detected with measures that focus on the severe end of the spectrum, for example diagnosed rates of depression (Oakley Browne et al., 2010).

4.4.2 Physical activity data

Respondents were asked to indicate how much time they had spent being physically active within the last seven days. From this information a binary variable was generated which indicated whether the respondent was meeting the recommended physical activity guidelines of at least 30 minutes of exercise on 5 or more days a week. For a complete list of physical activity questions refer to Appendix A.

4.4.3 Long-term health conditions

Survey respondents were asked to indicate whether they had any existing long-term health conditions. Included conditions were angina, arthritis, asthma (all types), diabetes, personal history of heart attacks, heart failure, high blood pressure, high cholesterol, personal history of strokes, chronic pain and mental health conditions. Data was represented as a binary with a 1 representative of an individual having any one or combination of the above conditions.

4.4.4 BMI data

Body Mass Index (BMI) was calculated for each respondent by obtaining height, weight and waist diameter measurements. A binary variable was then created indicating whether an individual was overweight or obese (1) or not (0) based on their BMI. The widely used BMI value of 25 was used as the cut of point between non-overweight and overweight individuals.

4.4.5 Age data

Age was provided in 5 year age groups from 15 – 65 years old. Three groups were created to reflect mental health disparities within age groups as by Nutsford et al. (2013). These groups were 15-44 years, 44-65 years and 65 years and above.

4.4.6 Ethnicity data

Ethnicity was provided in four categories: Māori, Pacific peoples, Asian and Other. Due to sample size restrictions ethnicity was recoded as a binary variable of Māori (1) and non-Māori (0).

4.4.7 Income data

Personal income was categorised into three ordinal groups:

1) Below $40,000 (approximately the national median income in 2010 for individuals earning a salary)
2) $40,000 – $70,000
3) $70,000 or more

4.5 **Review of chapter**

This chapter introduces the data sources used in the study and identifies the number of variables used as health outcomes and potential confounders. Area level data was pulled from a number of sources, most notably, the New Zealand 2006 census and from Koordinates.com, New Zealand's official geospatial data portal. All individual level data was obtained through the NZHS conducted in 2011/12.

Chapter 5: Creation of exposure variables and statistical analysis methodology

5.1 Creation of measures of exposure to natural environments

GIS techniques were used to derive a total of 33 different exposure measures of natural environments including visibility of, proximal access to and the quantity accessible, for each of the 46 population weighted MB centroids (from here on referred to as neighbourhood centroids). For a full list of exposure variables created refer to Appendix A. Figure 4 below shows the distribution of the population weighted neighbourhood centroids in the Wellington Region. Different exposure variables were created so that the associations between natural environments and health outcomes could be investigated separately through the two identified causal pathways of access and visual contact.

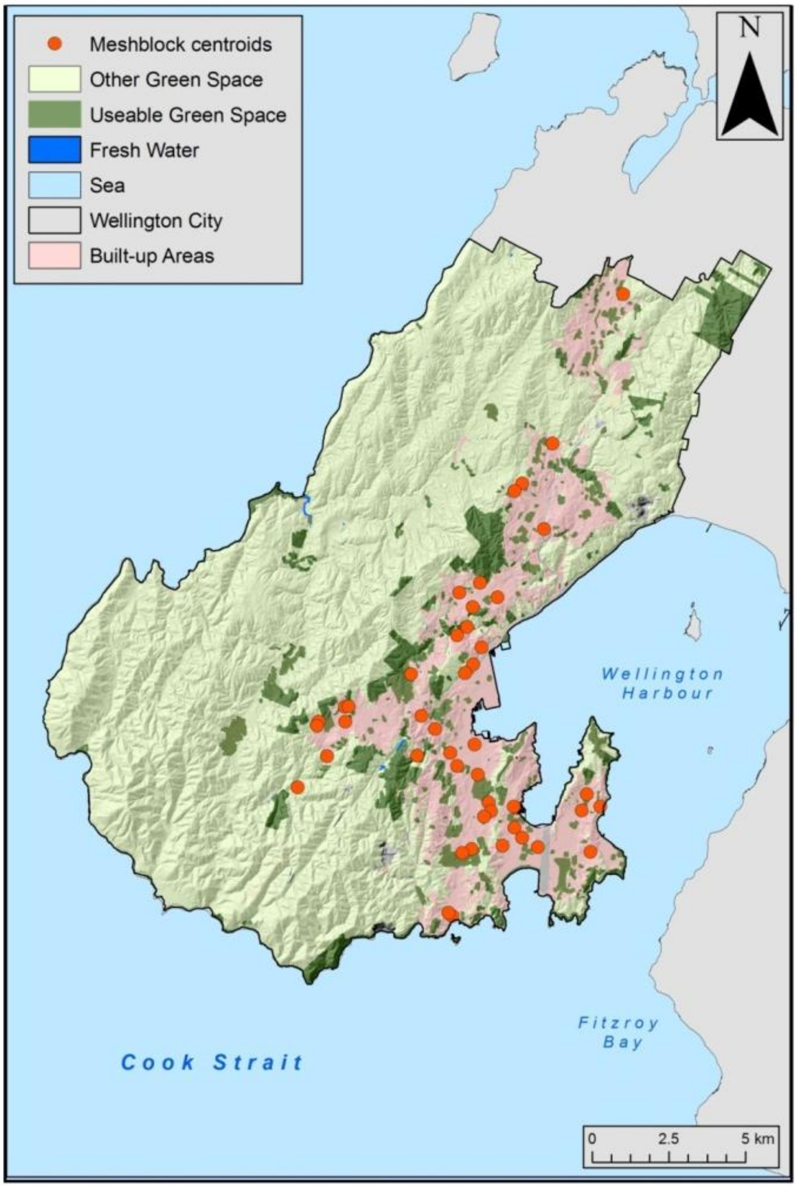


Figure 4: Distribution of population-weighted MB centroids in Wellington City from which all exposure variables were created.

5.1.1 Visibility exposure variables

22 exposure variables were created to measure the visibility of green space, blue space and total natural environments. Different visibility measurements were created which captured environments by area, distance from neighbourhood centroids, and visual quality. To avoid previously identified limitations with standard viewshed measures (see Chapter 3) a methodology similar to Domingo-Santos et al. (2011) calculation of the solid angle was implemented, to create a novel viewscape visibility measure of natural environments. In principle, this measure improves upon standard viewshed analysis by adjusting for the distance, slope, aspect and relative elevation of visible areas.

The first step was to derive which areas are visible from each neighbourhood centroid (or observer point) using the ArcGIS viewshed analysis tool (assuming midday visibility). By clipping visible areas to areas of green and blue space and summing the number of cells, the land area of visible natural environments for each neighbourhood centroid (km^2) was calculated. Before conducting this analysis, all neighbourhood centroids were given a vertical offset of two meters to simulate the view of a standing person within a first floor house. In order to account for some of the variation in visibility across a neighbourhood, the standard deviation of elevation values within each MB was used to identify those with highly variable terrain (n=13). These neighbourhoods were then manually inspected and assigned multiple new points to represent the different areas within the neighbourhood that had highly contrasting views. In total, viewshed analysis was run three times from each neighbourhood centroid, quantifying the visible areas of green space, blue space and total natural environments.

Next, the visible land area by 'visual quality' was calculated by clipping visible areas to a raster defining areas of varying quality. Visual quality was derived from the environment type and is a reflection of the aesthetic quality of nature, with areas such as native bush and blue space having relatively high aesthetic quality compared with low aesthetic environments such as low producing grass land (for example). This step differs from the total viewshed output above by quantifying the amount visible natural environments from neighbourhood centroids as aesthetically pleasing, moderately aesthetic or non-aesthetically pleasing.

The results of these procedures were variables representing total visible areas, and the area of visible locations by three categories of aesthetic quality from each neighbourhood centroid. However, for the reasons identified in Chapter 3 (section 3.1.2), these variables are recognised to be inaccurate representations of visible natural environments from the perspective of an individual standing at the centroid. Figure 5 highlights the difference between the viewshed representation of visible natural environments (which shows areas theoretically visible based on LoS analysis), and the view from a human perspective.

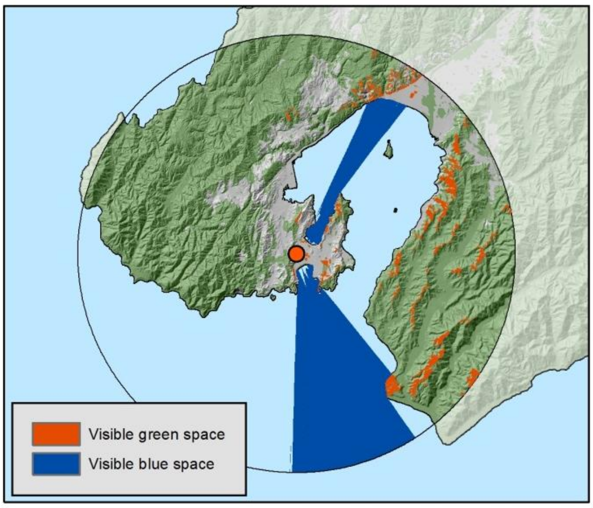


Figure 5: Illustrated difference in the viewshed representation of visible natural environments and visible natural environments form the perspective of an individual. Google Earth imagery shows the view from a human perspective looking South-south-east from the observer point. The significance of visible blue space is clearly over-exaggerated in the viewshed analysis output while the visual significance of the Rimutaka hills (green space) is under exaggerated.

There are a number of factors that are important to consider when creating visibility measures to accurately capture the view from the perspective of an individual. The 'visual significance' of terrain is a term that can be used to describe how influential an area is to one's perception of the environment. Slope, aspect, distance and elevation of visible areas all influence the 'visual significance' of observed features (for example, consider the visual significance between a nearby hill and a distant mountain range. While the latter may be much larger, the smaller, closer hill is likely to be more pronounced). In light of these factors, a new exposure variable was developed. This measure is termed a 'viewscape' and utilised the 'vertical degree' of visibility between every cell deemed visible and the neighbourhood centroid. The intended result of these viewscape analyses was to capture visible significance and more realistically measure visibility from the observer's perspective. This resulting measurement was termed the Visibility Index (VI).

5.1.2 Visibility Index (VI)

Two steps were taken to capture the visible significance of terrain. Firstly, the calculation of the vertical angle initially improved visibility measures by taking into account i) surface slope, ii) distance between the observer and visible terrain, and iii) elevation difference between the observer and visible terrain. Secondly, visibility measures are further improved by adjusting for the slope aspect of visible terrain (i.e. which direction the surface slope is facing relative to the observer). This two-step process was developed as an autonomous python script which iterated through each cell deemed visible from the ArcGIS viewshed tool, calculated its visual significance, and added it to a running total representing the visibility from each neighbourhood centroid. The following steps outline the procedure taken to calculate the visual significance of one cell.

The first step is to calculate the vertical angle between the eye ball of an observer and the upslope and down slope edge of the visible cell. The vertical angle is derived from calculating the length of the three sides of a theoretical non-right angle triangle (Figure 6):

i) 3D Distance between the observer's eye and the upslope edge of the sloped cell.
ii) 3D Distance between the observer's eye and the downslope edge of the sloped cell.
iii) 3D distance between the upslope and downslope edge of the cell.

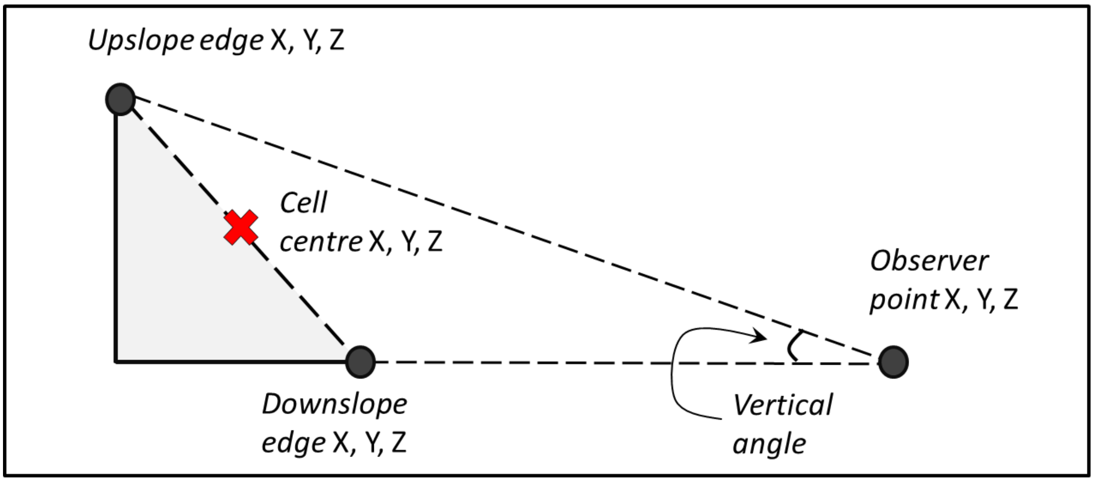


Figure 6: The cross section view of one visible cell from a neighbourhood centroid (or observer point). The X,Y,Z coordinates for the three points are required to calculate the vertical angle between an observer point and the cell.

Given all three side lengths, the interior angles of a non-right angle triangle can be calculated using the trigonometry laws of cosines. Using these laws, the angle between the upslope and downslope points of the visible cell and the eyeball of an observer are calculated (see Figure 6 for vertical angle). However, before these three distances can be calculated the X,Y,Z coordinates for the upslope and downslope points must be calculated relative to the cell centre (which is known). Firstly, the cell slope is estimated based on the elevation values of its neighbouring cells which allow the elevation change for the visible cell to be calculated using simple trigonometry (Figure 7).

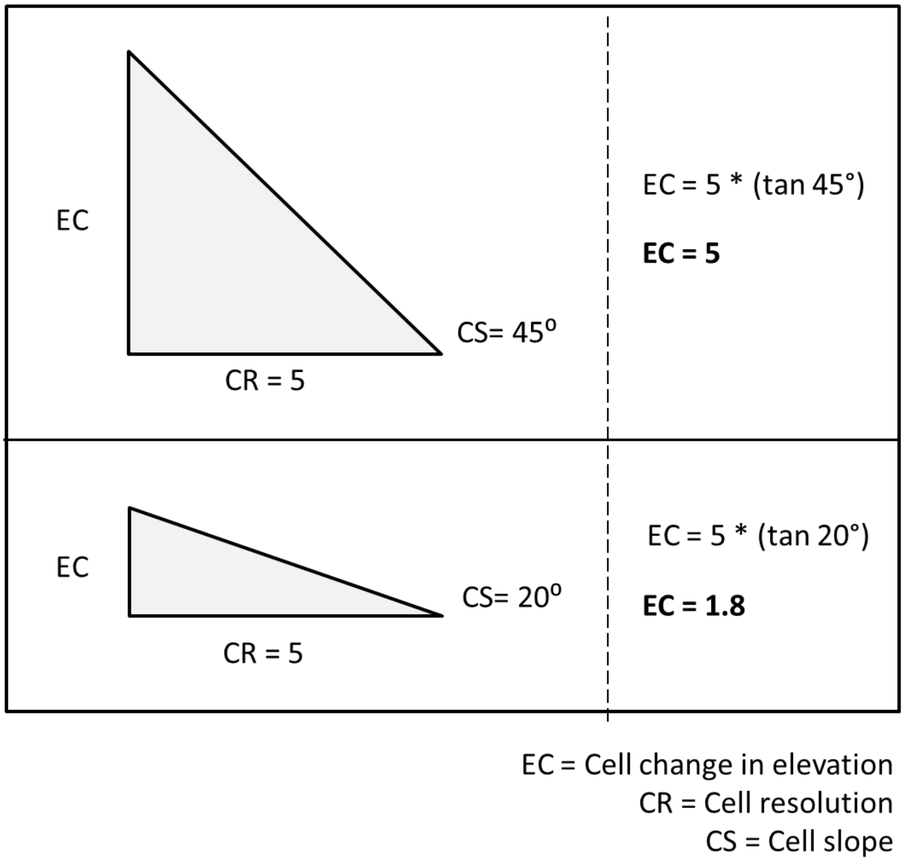
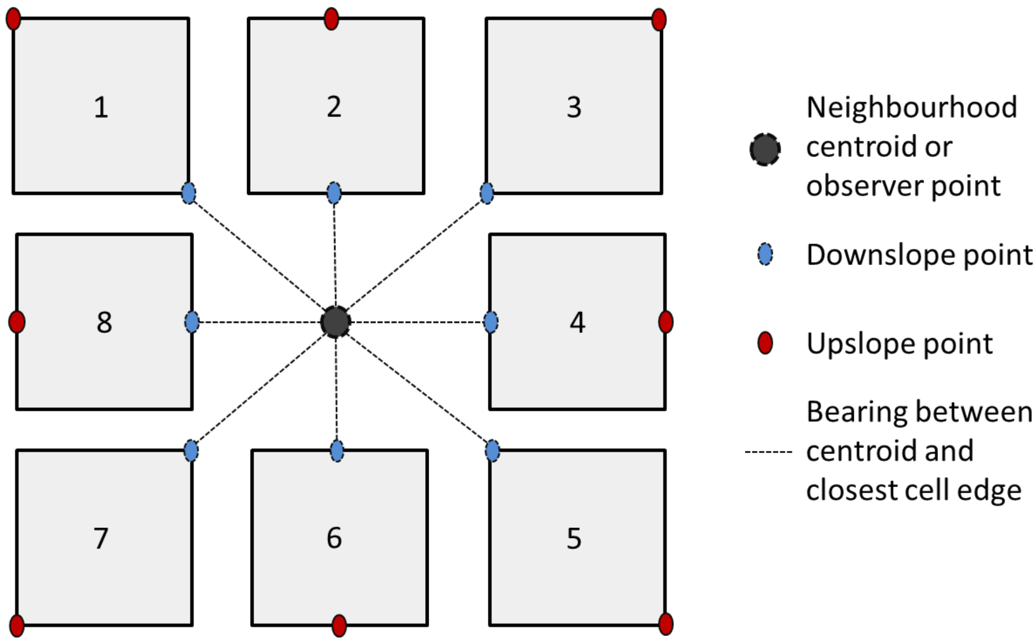


Figure 7: Cross section view showing the elevation change within two contrasting cells. Elevation change is calculated using the cell slope and cell resolution and right-angle trigonometry. Cell elevation change is required in order to calculate the Z coordinate of upslope and downslope cell edges.

Once the elevation change is known for the visible cell the upslope and downslope elevation (Z coordinate) is calculated by adding/subtracting half the height change to/from the cell centre elevation value. The calculation of the XY coordinates for the upslope and downslope coordinates are also derived relative the cell centre XY, however unlike the calculation of the Z coordinate, they are influenced by the bearing of the visible cell relative to the neighbourhood centroid or observer position (Table 8).



1) *Upslope X,Y = cell centroid - 2.5, cell centroid Y + 2.5*
Downslope X,Y = cell centroid + 2.5, cell centroid Y - 2.5

2) *Upslope X,Y = cell centroid, cell centroid Y + 2.5*
Downslope X,Y = cell centroid, cell centroid Y - 2.5

3) *Upslope X,Y = cell centroid + 2.5, cell centroid Y + 2.5*
Downslope X,Y = cell centroid - 2.5, cell centroid Y - 2.5

4) *Upslope X,Y = cell centroid + 2.5, cell centroid Y*
Downslope X,Y = cell centroid - 2.5, cell centroid Y

5) *Upslope X,Y = cell centroid + 2.5, cell centroid Y - 2.5*
Downslope X,Y = cell centroid - 2.5, cell centroid Y + 2.5

6) *Upslope X,Y = cell centroid, cell centroid Y - 2.5*
Downslope X,Y = cell centroid, cell centroid Y + 2.5

7) *Upslope X,Y = cell centroid - 2.5, cell centroid Y - 2.5*
Downslope X,Y = cell centroid + 2.5, cell centroid Y + 2.5

8) *Upslope X,Y = cell centroid - 2.5, cell centroid Y*
Downslope X,Y = cell centroid + 2.5, cell centroid Y

Figure 8: Calculations used to define new X and Y coordinates for the upslope and downslope points of visible cells. One of eight different calculations was used depending on the bearing of the visible cell relative to the neighbourhood centroids location.

Once all three coordinates identified in Figure 6 are known, the distance between them is calculated using the 3D point's distance formula:

$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \qquad \textbf{(1)}$$

As mentioned above, the law of cosines are used to calculate non-right angle triangle interior angles. The resulting vertical angle calculation, what is called the 'angle of visibility', is influenced by the cell slope and both distance and elevation relative to the position of the observer. Visible cells that are closer result in larger vertical angles while sloped cells may increase or decrease the vertical angle depending on their height relative to the viewpoint (see Figure 9 and Figure 10 for illustration).

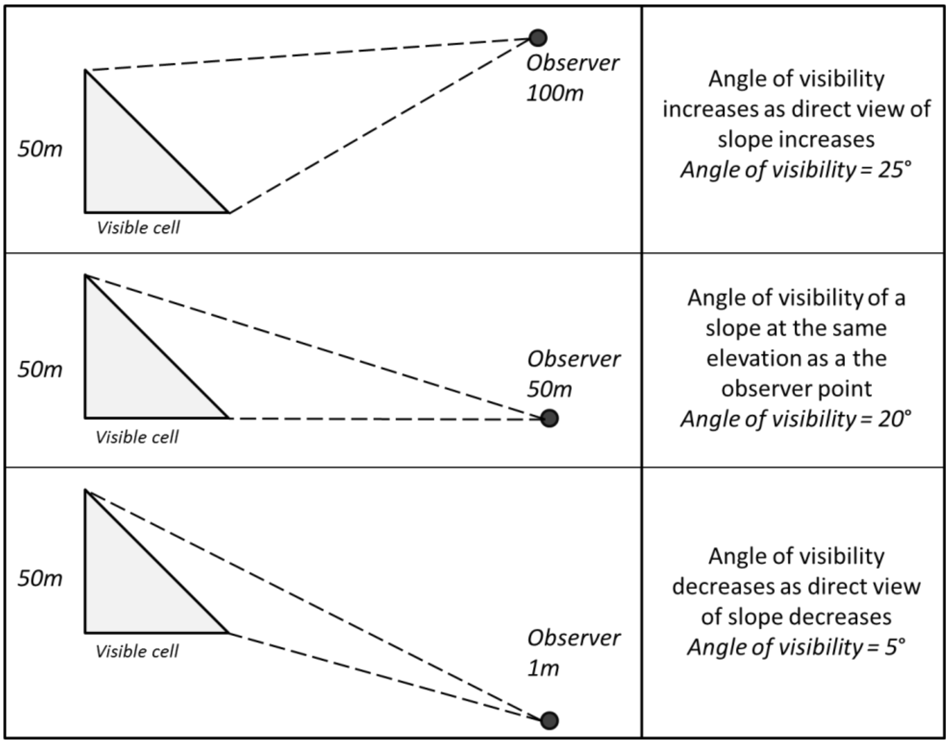


Figure 9: Cross-sectional view showing the influence of observer elevation above sea-level relative to the elevation of a visible cell on the angle of visibility.

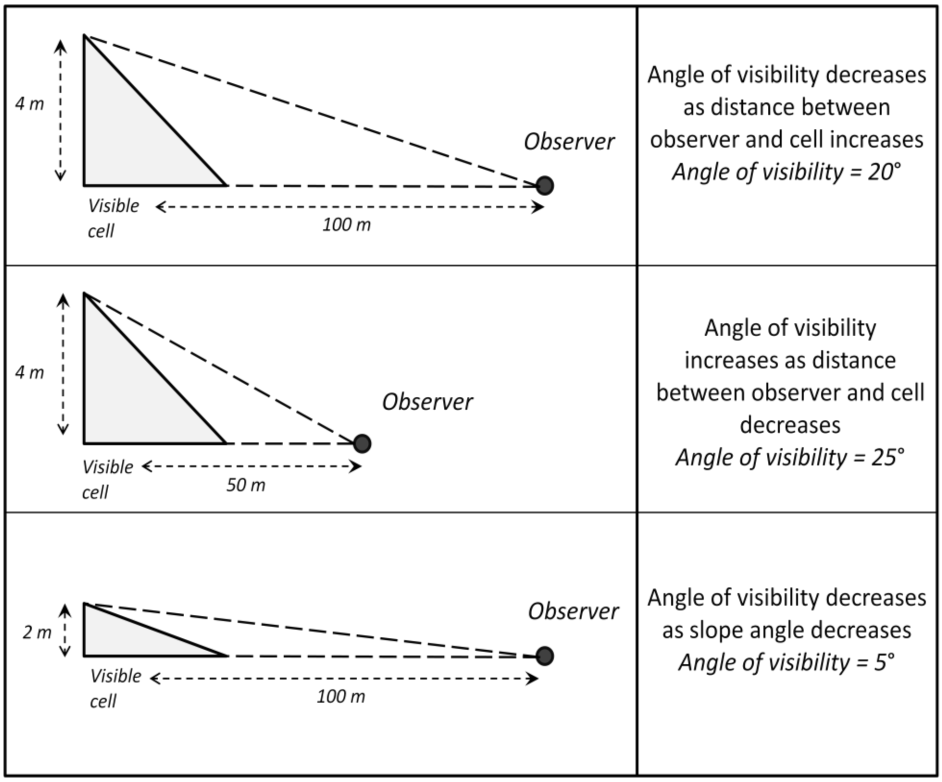


Figure 10: Cross-sectional view showing i) the influence distance between observer location and visible cells has on the angle of visibility and ii) the influence cell slope has on the angle of visibility.

The influence of slope aspect is the last factor to be accounted for and may have a significant influence. For example, a slope that is facing 45° relative to the observer has half the visual significance than a slope directly facing the observer. An adjusted measure of the angle of view is defined as:

$$\text{Adjusted Angle of Visibility} = Angle\ of\ Visibility\left(1 - \frac{Relative\ Aspcet}{90.0}\right) \qquad (2)$$

where relative aspect is the difference between cell aspect and cell bearing (i.e. measures to what degree the cell slope faces the observer). Only cells with a slope greater than 5 degrees were weighted by the aspect factor as near flat surfaces are consistently visible from all orientations. Cells that were within 50 m of the viewpoint were not included in analysis as they expressed a disproportionate number of degrees due to their close proximity.

This process of adjusting for each visible cells slope, distance, elevation and aspect was repeated and summed for each neighbourhood centorid, giving the total visual significance of natural environments from each of the 46 neighbourhood centroids. In order to measure whether the proximity of visible environments influenced health outcomes, the VI was divided into four distinct distance bands, each with a unique visual characteristic which may influence the psychological state of viewers. This was achieved by creating visibility measures for specific Euclidean distances for each neighbourhood centroid (as per the Hauichi theory). The first distance band included visible areas within 300m of the centroid and represents visible areas that can be clearly identified and recognised. The second distance band included areas between 300m and 3km and represents natural environments that are still visible but becoming unrecognizable. The third distance band included areas between 3km and 6km away. The final distance band included all visible areas between 6km and 15km. Each measure of visibility was then independently scaled from 0 to 100, where 100 represented the neighbourhood centroid which had the highest visual exposure to natural environments while 0 represents the centroid with the least.

5.1.3 Access exposure variables

In total, ten measures of proximal access to natural environments were created, by green space, blue space and total natural environments. Proximal accessibility was expressed as either the total distance (in metres) from each neighbourhood centroid to the closest polygon edge of green or blue space through the road network. Access to quantities of natural environments was generated by calculating the areal proportion of green space, blue space and total natural environments within 3km Euclidean buffer distances of each neighbourhood centroid. A 3km buffer was selected to reflect the distance travelled by 30 minutes of walking and represents access to natural environments in the greater neighbourhood.

5.1.4 Rescaling of exposure variables

In preparation for statistical analysis, each exposure variable was transformed to an ordinal scale between 1 and 10 representing 10 percentiles. This step was taken to strengthen the coefficient estimates produced in the statistical models.

5.2 **Statistical analyses**

5.2.1 Multiple imputation chained equations for missing data

From the 442 individuals in the study whom had an indicator of psychological stress, approximately 28% did not have complete values across all covariates due to missing income values (n=95, 20%) and BMI (n=63, 13%). Multiple imputations by chained equations (MICE) was used and data was assumed missing at random, to replace missing values with imputed values. Following White, Royston, & Wood's (2011) suggestion, 28 replicates of the dataset were created to reflect the percentage of missing data. To avoid bias, all independent and dependent variables (including health outcomes) were used in the final analytical models as variables for the chained imputation. Specifically, the following chained imputation regression models were fitted; a multinomial logistic model for the missing income variables and a logistic model for the missing overweight variable, as consistent with I. White et al., (2011). Regression results for three selected final analytical models were compared between non-imputed datasets and imputed datasets. It was found that beta coefficients changed <15% between models (see Appendix B). Thus, while descriptive statistics reported in Table 2 were calculated from the non-imputed dataset, all final analytical regression results were derived using the imputed values dataset.

5.2.2 Complex sampling design of the New Zealand Health Survey (NZHS)

In all analyses, adjustments were made for the complex multi-level sampling design of the NZHS. The study population was drawn from a subsample of the national survey and thus represents only one sampling stratum, or District Health Board. Therefore, no use was made of the jackknife weighting scheme, based on the national sample, provided by the Ministry of Health. Rather, Taylor series variance estimations were used and primary sampling unit cluster sampling design was specified. Please note that by specifying this multi-level sampling design, it was not necessary to specify multi-level regression models as the units of sampling and the area-level covariates in the models were the same geographic units.

5.2.3 Specification and variable selection for final analytical regression models

Regression models were used to examine any associations between exposures to natural environments and health outcomes while controlling for individual-level and area-level confounding variables. All final analytical regression models were fitted using the imputed dataset. This section introduces four models used to investigate the research questions outlined in Section 1.6. Directed acyclic graphs (DAGs) are used to display the hypothesised relationships between exposure variables, health outcomes and covariates and provide a theoretical basis to aid in the selection of variables to be used in statistical models. Also in this section, correlations between exposure variables are reported, and the measures used in final statistical analyses are identified following theoretical rationale.

In all models, four confounding factors (NZDep06, crime, personal income and population density) which are expected to be associated with both the measures of natural environment exposure and health conditions were identified. Māori, which are known to have higher psychological stress than other ethnic groups are controlled for through these confounders as the Māori ethnic group are also strongly correlated with deprivation and income (P. White et al., 2008). Sex and age are also known confounders in mental health research (Francis et al., 2012; Ministry of Health, 2012a; Richardson & Mitchell, 2010) and physical health research (Coombes et al., 2010; Hillsdon et al., 2006). In all models, NZDep06, neighbourhood crime rates, personal income and population density were included as ordinal variables while age and sex were both included as categorical binary variables.

Model 1: Visibility of Natural Environments and psychological stress

Model 1 is designed to explore the relationship between the measures of green and blue space visibility and mental health outcomes. Figure 11 identifies the relationship between visibility exposure variables, psychological stress and selected covariates.

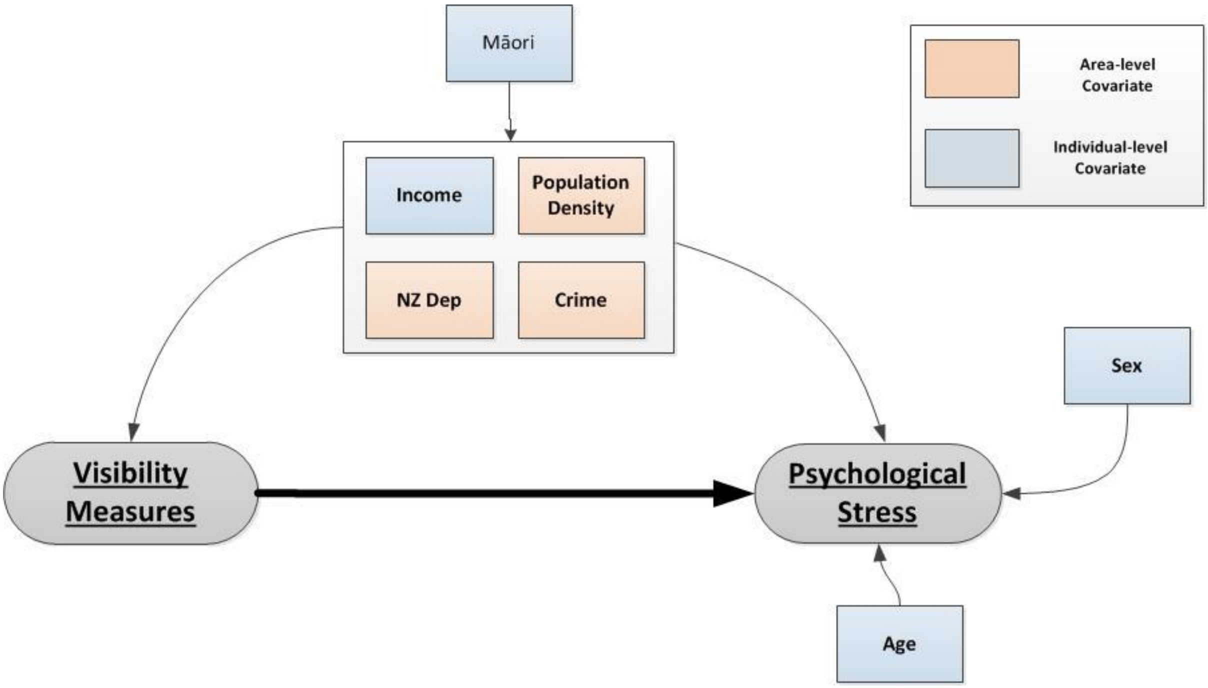


Figure 11: DAG showing the theoretical relationship between visible exposure variables, psychological stress and covariates.

In preliminary analyses, a significant Pearson's correlation between the VI for total blue space and blue space within the individual distance bands ($r > 0.7$, $p < 0.05$) was found. This was attributed to the contiguous nature of blue space. A large amount of visible blue space in the foreground is likely to correspond with a large amount of visible blue space in the background. In comparison, no significant correlation was detected between green space distance bands due to the complex terrain and irregular distribution of green areas across the study area. It was also found that measures of natural environment quality were correlated with measures of total visibility due to natural environment types showing limited spatial variation. In light of this preliminary analysis, seven final visibility exposure measures used in Model 1 were the VI scores for; total green space, green space within

300m, green space between 300m and 3km, green space between 3km and 6km, green space between 6km and 15km, total blue space, total natural environments.

The outcome measure of psychological stress was measured as an ordinal variable. Separate models were fitted for the outcome and each exposure variable, and each included all of the potential confounders. In total, seven linear regression models were fitted for the psychological stress outcome. Each model was adjusted for sex, age, income, socio-economic deprivation, population density and total crime.

Model 2a: Access to Natural Environments and psychological stress

Model 2a aims to explore the theoretical pathway between measures of access (both proximity and access to quantity) to natural environments and psychological stress (see Figure 12). In preliminary analyses of the exposure variables, a lack of variation between access measures to useable and total green space was observed (for both proximal access and access to quantity). This is attributed to the classification of green space which may have been too lenient towards useable green space as it included all green areas accessible by road. The five final access measures explored therefore only included proximal distance to total green space, proximal distance to blue space, access to quantities of green space within 3km, access to quantities of blue space within 3km, access to quantities of total natural environments within 3km.

Again, the outcome measure was psychological stress. Separate models were fitted for the outcome and each exposure variable, and each included all of the potential confounders. In total, five linear regression models were fitted for the psychological stress outcome. Each model controlled for sex, age, income, socio-economic deprivation, population density, crime rate, pollution levels.

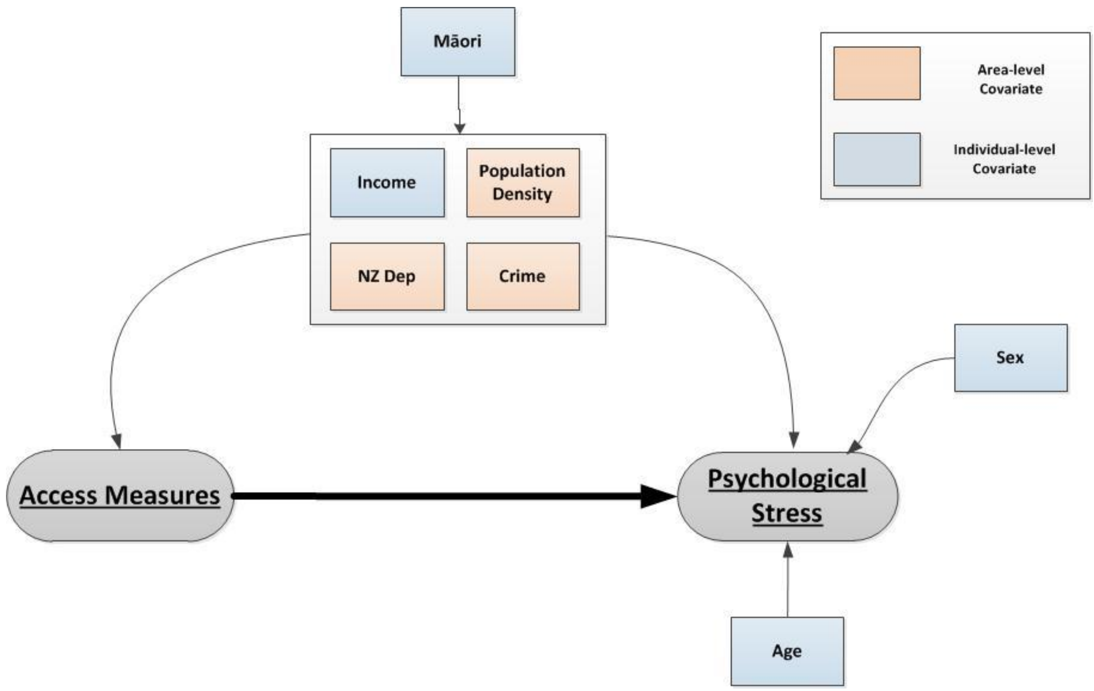


Figure 12: DAG showing the theoretical relationship between access exposure variables, psychological stress and covariates.

Model 2b: Access to Natural Environments and physical activity

Model 2b (Figure 13) aims to explore the relationship between measures of access to green and blue space and physical activity under the hypothesis that individuals with increased access to natural environments are more likely to be meeting recommended physical activity guidelines. In addition to the confounders highlighted above, obesity and long-term health conditions were expected to be the most significant barriers physical activity, but could also involve feedback. For example an obese individual may be less likely to exercise just as they may be obese because they exercise less often. Air pollution was also identified as a potential confounder, as people may be less likely to be active in more polluted conditions, while increased green space is associated with decreased air pollution (Richardson et al., 2010).

Using the same access measures as above, five separate models were fitted for the activity outcome and each exposure variable, and each included all of the potential confounders. In total, 5 logistic regression models were fitted for the binary physical activity indicator. Models were controlled for sex, age, income, socio-economic deprivation, long-term health conditions, population density, crime rate, pollution levels and obesity.

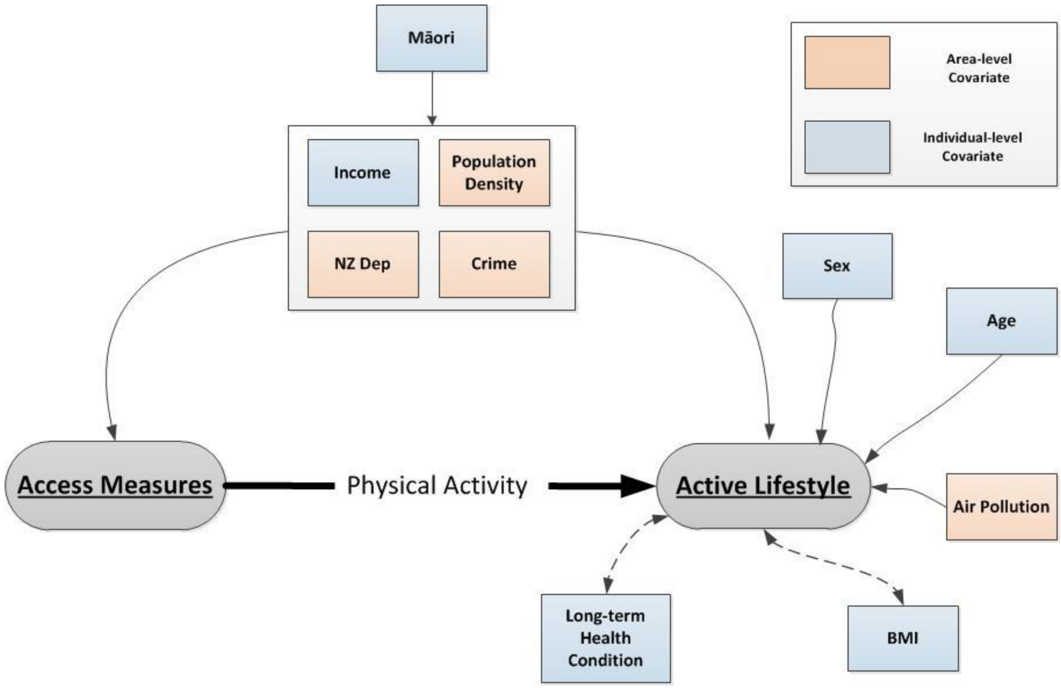


Figure 13: DAG showing the theoretical relationship between access exposure variables, physical activity and covariates.

Model 3: Physical activity and psychological stress

Model 3 aims to explore the relationship between measures of physical activity and psychological stress (Figure 14). In addition to the covariates included in all other models, this model includes BMI and long-term health conditions as confounding variables due to their obvious links to reduced physical activity and evidence of a relationship between BMI and stress (Torres & Nowson, 2007) and long-term health conditions and stress (Mental Health Commission, 2012).

Separate models were fitted for the psychological stress outcome and the measure of physical activity exposure variable, and each included all of the potential confounders. In total, one linear regression model was fitted for the binary measures of activity on the psychological stress outcome. The model controlled for sex, age, income, long term-health conditions, obesity, socio economic deprivation, population density, crime and air pollution.

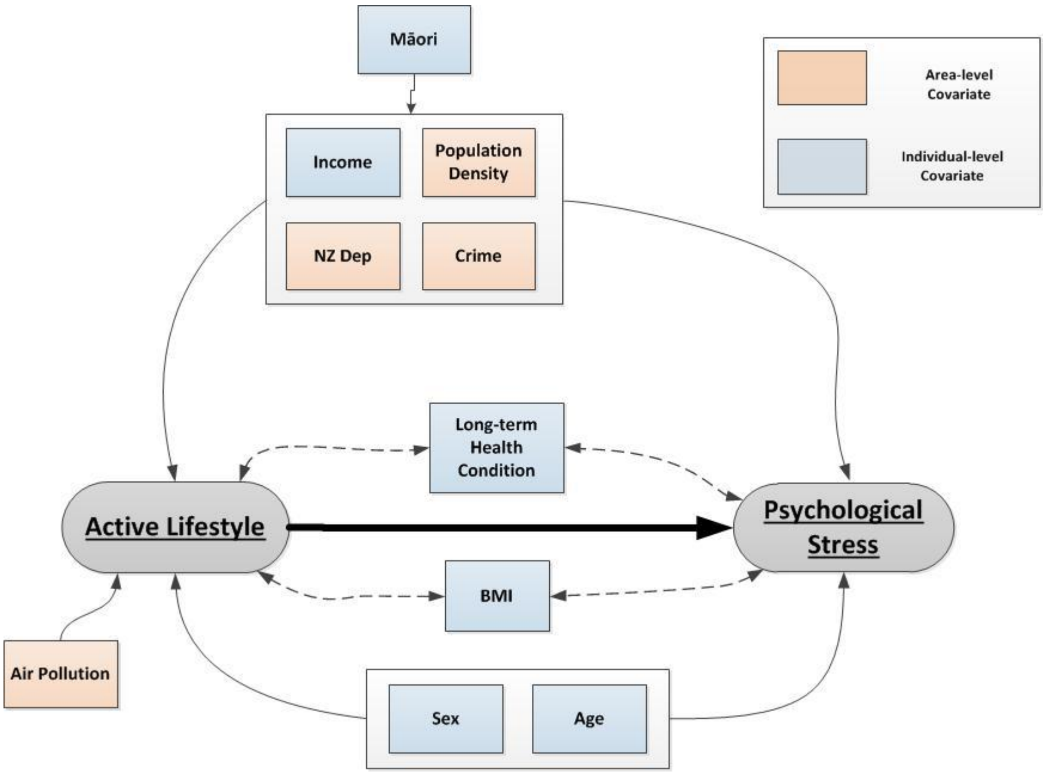


Figure 14: DAG model showing the theoretical relationship between physical activity, psychological stress and covariates.

5.3 Review of chapter

For a host of reasons identified in Chapter 3, standard viewshed analysis methods were not an appropriate method for assessing the visibility of natural environments from the perspective of a human individual. This prompted the development of the VI, which was able to account for visible terrain slope, aspect and distance from observer. Two measures of access were created. Proximal access was defined as the distance between neighbourhood centroids and nearest edge of a natural environment through a road network. Access to quantities was defined as the proportion of natural environment that fell within a 3km Euclidean distance buffer.

Due to a large number of missing data, the study utilised multiple imputations to predict missing data values. This technique allowed the full sample population to be included in analysis, rather than restricting it to individuals with complete data information. Finally, this chapter offered a theoretical basis for the selection of covariates and identified the exposure variables which were used in final analysis.

Chapter 6: Results

6.1 Descriptive characteristics of study population

In total, 460 individuals living in Wellington City participated in the NZHS. Of these participants, two had missing values for psychological stress and 16 had missing values for the indicator of physical activity and were thus omitted from analyses, leaving 442 individuals. As outlined in Section 5.2.1, missing values were also present for the variables personal income (n = 95) and BMI (n = 63) and multiple imputation using chained equations was conducted to estimate those missing values. However, for descriptive purposes, characteristics of respondents using the non-imputed dataset are reported, noting those with missing values. Table 2 below describes individual-level and neighbourhood characteristics for respondents by sex and the total study sample population.

Table 2: Descriptive statistics of the sample population. K10 values range from 0 – 40 with higher values indicative of more stress. NZDep06 values range from 1 – 10 with higher values indicating higher neighbourhood deprivation.

Variable	**Females**	**Males**	**Total**
Total	n = 260	n = 182	n = 442
Individual characteristics			
Sex (%)	58	41	100
Age (%)			
15-44	56	54	55
45-64	32	35	33
65+	12	12	12
Māori (%)	10	9	10
Income (%)			
$0 - $40,000	38	30	34
$40,000 - $70,000	26	15	21
$70,000 +	16	36	24
Missing	20	19	20
Health			
K10, mean *(sd)*	6.1 (5.2)	5.5 (4.5)	5.8 (4.9)
Obese (%) No	30	36	33
Obese (%) Yes	51	58	54
Obese (%) missing	18	60	13
Active Lifestyle (%)	39	38	39
Long term Health Condition (%)	53	45	50

Continued below

Area-level			
Total visible green space*, mean (sd)	30 (28)	33 (29)	31 (27)
visible green space < 300m*, mean (sd)	9 (18)	9 (20)	8 (19)
visible green space between 300m & 3km*, mean (sd)	29 (28)	29 (27)	29 (28)
visible green space between 3km & 6km*, mean (sd)	8 (15)	9 (14)	9 (14)
visible green space between 6km & 15km*, mean (sd)	5 (17)	9 (24)	7 (20)
Total visible blue space*, mean (sd)	4 (17)	7 (24)	5 (20)
Total visible natural environments*, mean (sd)	7 (17)	11 (24)	9 (20)
Distance to nearest green space, mean (sd)	158 (180)	169 (202)	162.4 (189)
Distance to nearest blue space, mean (sd)	2222 (1562)	2306 (1610)	2256 (1581)
Green space within 3km (%)	42 (22)	42 (23)	42 (22)
Blue space within 3km (%)	19 (17)	19 (17)	19 (17)
Natural environments within 3km (%)	62 (13)	61 (13)	61 (13)
NZDep06, mean (sd)	5 (2)	4 (2)	5 (2)
Population density (km2), mean (sd)	5535 (3827)	5020 (3571)	5323 (3729)
Air pollution (PM_{10} μgm^{-3}), mean (sd)	12.(6)	12 (6)	12 (6)
Crime rate per 100 000, mean (sd)	10 (78)	10 (8)	10 (8)

* Possible value ranges 0 - 100

6.2 Individual-characteristics and psychological stress

Table 3 shows that psychological stress was slightly higher amongst females than males with respective average K10 scores of 6.1 and 5.5. The youngest age group in the study (15-44 years) was found to have the highest average psychological stress, with a mean Kessler score of 6.4, a score that suggests the individual is at moderate risk of having a mental disorder. Respondents 65 years and older had similar indicators of stress with a mean K10 score of 6. The middle age group (45-64 years) had the lowest indicator of stress with a mean K10 score of 4.8. Psychological stress was higher on average amongst Māori than non-Māori with a K10 score of 8.9 vs. 5.5 (Table 3). Indicators of psychological stress varied with personal income with average K10 scores decreasing from 6.8 in the lowest income group to 4.2 in highest income group. The group of respondents who declined to provide their personal income had the highest average K10 score at 6.7. Both this group and the group earning below $40,000 (approximately the median annual salary in New Zealand for individuals earning a salary in 2010) (Statistics New Zealand, 2010)) had scores above 6 indicating that individuals within these groups had moderate likelihoods of experiencing mental disorders. Table 3 shows that individuals meeting physical activity guidelines had slightly increased indicators of psychological stress (K10 scores of 6.1 vs. 5.6 respectively). Overweight/obese individuals were found to have similar average K10 scores to non-obese or overweight individuals (5.7 vs. 6). As expected, psychological stress was more common amongst individuals who reported to have a long-term health condition than those without (6.6 and 6.1 respectively).

6.3 Individual-characteristics and physical activity and obesity

Table 3 shows 39% of all people surveyed were meeting physical activity guidelines, a percentage consistent through males and females. The youngest age group was the most active with 42% meeting physical activity guidelines, followed by 45-64 year olds (38%) and 65 years and above (26%). This was reflected by the proportion of overweight/obese individuals in each age group which increased with older age groups (Table 3). Māori were more likely to meet physical activity guidelines than non-Māori (52% vs. 38%), however were also more likely to be obese (74% vs. 61%). The missing income group was the most active group with 45% of individuals meeting physical activity guidelines. The remaining income bands were found to be decreasingly active with increasing annual incomes with 33% of the top earners ($70,000+ annually) meeting physical activity guidelines compared with 40% of individuals earning below $40,000. Whether or not individuals met the recommended physical activity guidelines appeared to have no influence on obesity with only a 1% difference between the two groups. The missing BMI group were the least physically active at 32% while the prevalence of individuals meeting physical activity guidelines was 40% for both the overweight/obese and non-overweight/obese groups. Interestingly however, the group with long-term health conditions were found to be more active with 43% of individuals meeting physical activity guidelines vs. only 35% amongst the group with no long term health conditions. Overweight/obesity was much more prevalent amongst the group with long term health conditions at 70% vs. 55% for those without.

Table 3: Health outcomes by selected population characteristics

Variable	N	K10, mean (sd)	Active, %	Obesity, %
Total study population	442	5.83 (4.9)	39	62
Sex				
Female	260	6.1 (5.2)	39	63
Male	182	5.45 (4.5)	38	62
Age				
15-44	243	6.42 (5.1)	42	59
45-65	146	4.79 (4.3)	38	65
65+	53	6.03 (5.3)	26	72
Ethnicity				
Māori	42	8.86 (7.5)	52	74
Non-Māori	400	5.51 (4.5)	38	61
Income				
$0-$40,000	152	6.77 (5.1)	40	57
$40,000-$70,000	95	5.39 (4.1)	38	59
$70,000 +	108	4.21 (3.3)	33	71
Missing	87	6.68 (6.5)	45	64
Activity				
Regularly Active	172	6.14 (5.1)	100	63
Not Regularly Active	270	5.64 (4.8)	0	62
Obesity				
Overweight or Obese	239	5.71 (4.9)	40	100
Not Overweight	144	5.96 (4.8)	40	0
Missing	59	6.02 (5.4)	32	-
Long-term health condition				
Yes	219	6.57 (5.4)	43	70
No	223	5.11 (4.3)	35	55

6.4 Study population and the visibility of natural environments

Table 4 below shows mean and standard deviation values for the VI by income and age categories and neighbourhood socio-economic deprivation. For each measure of visible environments (green space, blue space and total natural environments) higher earners tended to live in neighbourhoods with increased views while individuals who didn't report their income tended to be living in neighbourhoods with the least visible natural environments. On average the 15-44 year old age group lived in neighbourhoods with the lowest visibility of natural environments while the oldest age group (65 years plus) tended to live in neighbourhoods with the most views of nature. Mean VI values were decreased in neighbourhoods with high deprivation compared to neighbourhoods with low deprivation for all three measures of natural environments. For example the least deprived neighbourhoods scored VI values for green space of 59 vs. 12 for the most highly deprived neighbourhoods.

Table 4: Income groups, age groups and socio-economic deprivation on neighbourhood visibility of green space, blue space and total natural environments.

	N	Visible green space		Visible blue space		Visible natural environments	
		mean	*(sd)*	mean	*(sd)*	mean	*(sd)*
Income							
$0-$40,000	152	29.6	(27.8)	5.6	(21.2)	8.6	(21.1)
$40,000-$70,000	95	32.4	(27.5)	3.5	(14.5)	7.1	(14.6)
$70,000+	108	37.9	(30.6)	10.9	(27.7)	14.3	(27.2)
Missing	87	25.5	(22.8)	2.6	(14.0)	5.4	(14.1)
Age Band							
15-44	243	30.7	(28.4)	5.6	(21.3)	8.7	(21.1)
45-64	146	32.3	(26.1)	5.7	(19.4)	9.0	(19.3)
65+	53	32.1	(29.9)	7.4	(22.1)	10.5	(22.2)
Deprivation							
1 (low)	100	58.9	(28.3)	17.6	(34.2)	22.8	(32.9)
2	91	32.7	(28.4)	5.5	(22.9)	8.8	(22.3)
3	91	30.7	(19.9)	0.1	(0.2)	3.8	(2.4)
4	80	15.8	(16.0)	4.0	(9.6)	5.5	(10.3)
5 (high)	80	11.8	(9.7)	0.0	(0.0)	1.4	(1.2)

6.5 Study population and access to natural environments

Table 5 and Table 6 below show levels of access to natural environments by categories of income, age and neighbourhood socio-economic deprivation. The average neighbourhood distance to nearest green space and all natural environments was smallest (indicating better proximal access) for individuals earning in the middle income band ($40,000 - $70,000) (Table 5). Individuals earning less than the 2010 median salary had the least neighbourhood proximal access (189m and 186m respectively) followed by individuals earning $70,000 and above (153 vs. 147m). Individuals who did not report their income had an average neighbourhood proximal distance to green space of 169m. Contrastingly, proximal access to blue space was the greatest for individuals earning below the 2010 median salary at an average distance of 2259m. Individuals in the two income groups earning $40,000 or above and the group who did not report their income, all had similar levels of proximal access to blue space (Table 5). Table 6 shows that access to the quantity of green space and all natural environments by income groups were found to be similar to the proximal access measures. Again, individuals earning between $40,000 and $70,000 had the greatest access to quantities of green and all natural environments, while individuals earning below $40,000 had the least access. Access to quantities of blue space was similar through all income groups' with a coverage between 19% and 20% within a 3km radius. Individuals who did not report their income had slightly less access to quantities of blue space at 17% (Table 6).

Access to natural environments was found to vary more amongst age groups than income groups. Both proximal access and access to quantities of green space were decreased for the 65+ age group in comparison to the other two age groups. This pattern was reversed for access measures to blue space. Average proximal access and access to quantities of blue space was greatest for the 65+ age group. The average neighbourhood proximal access to blue space decreased from 2 252m to 2 014 between the youngest and oldest age groups (Table 5) while blue space coverage decreased from 28% to 17%. Due to the opposite patterns exhibited between age groups and access to quantities of blue and green space, access to total natural environments was not seen to vary between age groups (Table 6).

Proximity access to green spaces varied with neighbourhood socio-economic deprivation (Table 5). Neighbourhoods with either the highest or lowest levels of deprivation had the least proximal access to green space (250m and 240m respectively) compared to the other three mid-range groups (<127m). Access to quantities of green space was decreased for increasingly deprived neighbourhoods with a green space coverage decrease of 44% to 30% between the least and most deprived neighbourhoods. Average proximity to blue space varied strongly through levels of neighbourhood deprivation (Table 5). Neighbourhood proximal access to blue space increased with increasing deprivation showing that more deprived communities had greater access to blue spaces (a decrease of 3 247 to 1 363m between the least and most deprived neighbourhoods. Average access to blue space quantities was slightly increased for the more deprived neighbourhoods, however the most deprived and least deprived neighbourhoods had similar levels of blue space within 3km of neighbourhood centroids (16% and 18% respectively). The proportion of all natural environments within a 3km radius of neighbourhood centroids weakly supports the notion that more deprived neighbourhoods have decreased access to quantities of green and blue spaces overall with a decreased coverage of 46% from 62% between the most and least deprived neighbourhoods.

Table 5: Income groups, age groups and socio-economic deprivation on neighbourhood proximal access of green space and blue space.

	N	Distance to green space		Distance to blue space	
		mean	*(sd)*	mean	*(sd)*
Income					
$0-$40,000	152	189	(195)	2110	(1538)
$40,000-$70,000	95	128	(165)	2313	(1553)
$70,000+	108	153	(201)	2303	(1647)
Missing	87	169	(189)	2395	(1610)
Age Band					
15-44	243	156	(177)	2252	(1526)
45-64	146	145	(178)	2353	(1653)
65+	53	242	(254)	2014	(1629)
Deprivation					
1 (low)	100	250	(289)	3247	(1641)
2	91	88	(98)	2723	(1611)
3	91	106	(107)	1940	(1415)
4	80	127	(172)	1743	(1512)
5 (high)	80	240	(129)	1363	(611)

Table 6: Income groups, age groups and socio-economic deprivation on neighbourhood access to quantities of green space, blue space and total natural environments.

	N	Quantity of green space		Quantity of blue space		Quantity of natural environments	
		mean	*(sd)*	mean	*(sd)*	mean	*(sd)*
Income							
$0-$40,000	152	41	(22)	20	(18)	61	(14)
$40,000-$70,000	95	44	(24)	19	(19)	64	(13)
$70,000+	108	42	(23)	20	(18)	62	(13)
Missing	87	44	(22)	17	(15)	61	(14)
Age Band							
15-44	243	44	(23)	17	(16)	61	(14)
45-64	146	43	(24)	21	(19)	63	(13)
65+	53	34	(19)	28	(19)	62	(12)
Deprivation							
1 (low)	100	44	(17)	18	(14)	62	(10)
2	91	55	(26)	12	(13)	68	(15)
3	91	40	(23)	28	(25)	68	(8)
4	80	41	(27)	23	(21)	64	(15)
5 (high)	80	30	(6)	16	(4)	46	(4)

6.6 Research Question 1: Is visibility of natural environments associated with psychological stress?

6.6.1 Bivariate analysis

Table 7 below shows the average K10 values by quintiles (1 = low, 5 = high) of different measures of the visibility of natural environments. Average K10 values were notably lower for neighbourhoods with the highest exposure to distant green spaces (i.e. beyond 3km), blue space and total natural environments compared to the neighbourhoods with decreased views. Mean K10 scores did not vary between individuals living in neighbourhoods with the greatest or least exposure to green space within 3km. As there were no visible blue spaces from many neighbourhoods, the first four quartiles were collapsed into one. A decrease in mean K10 scores was observed in neighbourhoods that did have visible blue space environments. Likewise, individuals living in neighbourhoods with more visible blue *and* green space had decreased indicators of stress when comparing neighbourhoods with the most and least amount of visible natural environments. The findings observed in Table 7 infer that individuals living in neighbourhoods with increased distant green space or total blue space have decreased levels of stress compared with individuals living in neighbourhoods with reduced views of distant green space or total blue space.

Table 7: Mean Kessler scores indicating psychological stress by quintiles of seven visibility exposure variables for study participants. K10 values range from 0 – 40 with higher values indicative of increased psychological stress.

	K10, mean (sd) by quintiles				
Exposure variable	1 (low)	2	3	4	5 (high)
Total Green Space	6.5 (4.1)	5.9 (6.0)	5.1 (5.2)	6.4 (5.3)	5.3 (3.7)
Green Space < 300m	6.2 (4.5)	6.2 (4.5)	5.3 (5.7)	4.7 (4.5)	6.7 (5.3)
Green Space (300m - 3km)	5.7 (4.3)	6.2 (5.8)	4.8 (5.1)	6.3 (5.4)	6.1 (3.6)
Green Space (3km - 6km)	6.0 (5.1)	8.3 (6.6)	7.4 (5.0)	5.0 (4.5)	4.1 (3.7)
Green Space (6km - 15km)	6.0 (4.1)	5.5 (5.1)	6.4 (5.2)	6.9 (5.4)	4.1 (4.7)
Total Blue Space	6.2 (4.9)	6.2 (4.9)	6.2 (4.9)	6.2 (4.9)	4.0 (4.7)
Total Natural Environments	6.5 (4.1)	6.3 (5.8)	4.5 (5.1)	6.8 (4.8)	4.5 (4.2)

6.6.2 Results of regression models

The regression estimates for Model 1a presented in Table 8, indicate a lack of a significant association between total green space visibility (independent variable of interest) and K10 scores (dependent variable) after confounder adjustment ($\beta = -0.14$, $p = 0.15$). In Model 1b however, a significant negative association was found, where increased total blue space visibility was associated with reduced K10 scores, or decreased psychological stress ($\beta = -0.32$, $p < 0.001$). This suggests that for each 10% increase in the visibility of total blue space a decreased K10 score of 0.32 is expected. In Model 1c, a statistically significant negative association between total natural environments visibility and K10 scores was found after confounder adjustment ($\beta = -0.23$, $p = 0.01$). This finding suggests that for every 10% increase in visible exposure to all natural environments there is an associated expected decrease of 0.23 in K10 scores.

In Models 1a through to 1c, personal income had a significant association with K10 scores. Individuals with higher incomes exhibited lower levels of stress in all three models ($\beta > -0.9$, $p < 0.01$). Neighbourhood deprivation was significantly, positively associated with K10 scores in Model 1b ($\beta = 0.23$, $p = 0.05$), indicating that individuals from deprived neighbourhoods have increased stress. While population density was significant in Models 1a - 1c ($p <= 0.05$) they all exhibited weak associations ($\beta < 0.001$). Sex, age and crime rates were not significantly associated with K10 scores.

Table 8: Results from three multiple regression models showing the association between 10 percentiles of i) total visible green space, ii) total visible blue space and iii) total visible natural environments and psychological stress (dependent variable) while controlling for selected covariates. K10 values range from 0 – 40 with higher values indicative of increased psychological stress.

Outcome = K10 Score	Model 1a: Total Green Space					Model 1b: Total Blue Space					Model 1c: Total Natural Environments				
Variables	**β**	**SE**	**P**	**95% CI**		**β**	**SE**	**P**	**95% CI**		**β**	**SE**	**P**	**95% CI**	
All Green Space	-0.14	0.10	0.15	-0.33	0.05										
All Blue Space						-0.32	0.07	<0.001	-0.45	-0.19					
Total Natural Environments											-0.23	0.09	0.01	-0.40	-0.05
Sex	-0.54	0.52	0.30	-1.57	0.48	-0.42	0.50	0.40	-1.40	0.56	-0.52	0.52	0.31	-1.54	0.49
Age	-0.06	0.08	0.46	-0.23	0.10	-0.04	0.08	0.60	-0.20	0.12	-0.06	0.08	0.47	-0.22	0.10
Income	-1.02	0.35	0.00	-1.70	-0.33	-0.90	0.33	0.01	-1.56	-0.25	-0.99	0.34	<0.001	-1.66	-0.31
NZDep06	0.15	0.14	0.26	-0.12	0.43	0.23	0.12	0.05	0.00	0.47	0.13	0.13	0.33	-0.13	0.39
Population Density	0.00	0.00	0.04	<0.001	<0.001	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.02	<0.001	0.00
Crime Rate	-0.03	0.03	0.36	-0.09	0.03	-0.01	0.03	0.76	-0.06	0.05	-0.04	0.03	0.26	-0.10	0.03

When assessing green space visibility exposure according to distance bands (Table 9), no significant associations between the amount of visible green spaces within 300m (independent variable of interest in Model 1d) and within 300m-3km (independent variable of interest in Model 1e) and K10 scores were found. In contrast, the amount of visible green space at distances 3 - 6km (Model 1f) was found to be significantly, negatively associated with K10 scores ($\beta = -0.21$, $p = 0.01$). This means that increased visible green space 3-6km away is associated with reduced psychological stress. Model 1g found visible green space at distances 6-15km away to also be negatively associated with psychological stress ($\beta = -0.15$) and was approaching statistical significance ($p = 0.06$).

In all regression models presented in Table 9, decreased personal income was significantly associated with higher K10 scores (increased stress) as found in Table 8. Sex, age, neighbourhood deprivation, population density and crime rates were not significantly associated with K10 scores.

Table 9: Results from four multiple regression models showing the association between 10 percentiles of i) visible green space within 300m, ii) visible green space at distances 300m – 3km, iii) visible green space at distances 3km-6km and iv) visible green space at distances 6km-15km and psychological stress (dependent variable) while controlling for selected covariates. K10 values range from 0 – 40 with higher values indicative of increased psychological stress.

Variables	Nearby Green Space									
	Model 1d					Model 1e				
	β	SE	P	95% CI		β	SE	P	95% CI	
Greenery within 300m	0.03	0.08	0.70	-0.13	0.19					
Greenery between 300m & 3km						0.06	0.09	0.46	-0.11	0.24
Sex	-0.53	0.53	0.31	-1.56	0.50	-0.54	0.52	0.30	-1.56	0.49
Age	-0.06	0.09	0.50	-0.23	0.11	-0.07	0.08	0.42	-0.23	0.10
Income	-1.05	0.35	<0.001	-1.74	-0.36	-1.03	0.35	<0.001	-1.72	-0.34
NZDep06	0.22	0.13	0.10	-0.04	0.47	0.23	0.13	0.09	-0.03	0.49
Population Density	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.16	0.00	0.00
Crime Rate	-0.02	0.03	0.48	-0.09	0.04	-0.02	0.03	0.59	-0.08	0.05
Variables	**Distant Green Space**									
	Model 1f					**Model 1g**				
	β	**SE**	**P**	**95% CI**		**β**	**SE**	**P**	**95% CI**	
Greenery between 3km & 6km	-0.21	0.08	0.01	-0.38	-0.05					
Greenery between 6km & 15km						-0.15	0.08	0.06	-0.31	0.01
Sex	-0.43	0.51	0.41	-1.43	0.58	-0.49	0.51	0.34	-1.49	0.52
Age	-0.06	0.08	0.46	-0.23	0.10	-0.07	0.08	0.40	-0.23	0.09
Income	-0.99	0.34	<0.001	-1.66	-0.33	-0.96	0.35	0.01	-1.65	-0.28
NZDep06	0.16	0.13	0.21	-0.09	0.41	0.18	0.12	0.14	-0.06	0.42
Population Density	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.12	0.00	0.00
Crime Rate	-0.07	0.03	0.05	-0.14	0.00	-0.02	0.03	0.47	-0.08	0.04

6.7 Research Question 2: Is access to natural environments associated with psychological stress or physical activity?

6.7.1 Bivariate analysis

Table 10 below shows the mean K10 score values and average proportion of individuals meeting physical activity guidelines by quintiles of increasing access (1 = reduced access, 5 = increased access) for five exposure variables to natural environments. Average K10 values were lower for residents in neighbourhoods with the best proximal access to green spaces compared to neighbourhoods with the least proximal access (4.7 vs. 6.9 respectively). In addition, individuals living in neighbourhoods with either the best or the least proximal access to blue space, on average, had the lowest K10 scores compared to individuals in neighbourhoods with moderate levels of access to blue space.

Surprisingly, Table 10 shows that those living in neighbourhoods with the best access to quantities of green space within 3km have higher average K10 scores (increased stress) in comparison to those living in neighbourhoods with the least amount of nearby green space (6.7 and 5.9 respectively). This pattern is reversed for access to quantities of blue space. Those living in neighbourhoods with the most blue space within 3km have lower average K10 values (decreased stress) than those living in neighbourhoods with the least access to quantities of blue space (5.2 and 6.3 respectively). Mean K10 scores were similar between those living in neighbourhoods with the most and least access to quantities of total natural environments, a reflection of the contrasting trends exhibited between access to quantities of blue space and green space.

Table 10: Mean Kessler scores indicating psychological stress and proportion of people meeting physical activity guidelines by quintiles of the five access exposure variables for study participants.

Exposure variable	Quintiles	K10, mean (sd)	Active (%)
Proximity to green space	1 (low)	6.9 (3.8)	44
	2	5.1 (5.0)	42
	3	6.8 (6.2)	44
	4	6.0 (4.7)	37
	5 (high)	4.7 (4.4)	30
Proximity to blue space	1 (low)	5.1 (4.3)	34
	2	6.2 (5.4)	39
	3	5.8 (4.2)	39
	4	6.8 (5.1)	48
	5 (high)	5.1 (5.2)	34
Green space coverage within 3km	1 (low)	5.9 (5.2)	37
	2	6.8 (5.2)	44
	3	4.8 (4.9)	33
	4	5.0 (4.6)	40
	5 (high)	6.7 (4.5)	41
Blue Space coverage within 3km	1 (low)	6.3 (4.7)	42
	2	5.1 (4.6)	35
	3	6.8 (5.2)	42
	4	5.6 (4.6)	34
	5 (high)	5.2 (5.4)	41
Total natural environments coverage within 3km	1 (low)	6.5 (5.2)	37
	2	6.1 (5.5)	40
	3	5.7 (4.1)	31
	4	4.5 (4.5)	40
	5 (high)	6.3 (4.9)	45

Also surprisingly, neighbourhoods with the best proximal access to green space were found to have lower proportions of individuals meeting recommended physical activity guidelines compared to neighbourhoods with the least proximal access (30% vs. 44% respectively) indicating that people living in neighbourhoods farther away from green spaces tend to be more active than those living nearer to green environments (Table 10). The proportion of people meeting recommended physical activity guidelines was the same between neighbourhoods with the most and least proximal access to blue space, at 34%. Those living in neighbourhoods with moderate proximal access to blue space tended to be more active (>39% meeting physical activity guidelines).

Neighbourhoods with the highest coverage of green space within 3km had slightly increased proportions of regularly active individuals than neighbourhoods with the least access to green space within 3km (41% vs. 37%). Similarly, individuals were more likely to be meeting recommended physical activity guidelines in neighbourhoods with the best access to quantities of all natural environments within 3km compared with individuals from neighbourhoods with the least access to all natural environments (45% vs. 37%). The physical activity of individuals did not vary between neighbourhood access to quantities of blue space.

6.7.2 Results of regression models

Proximal access to green space (Model 2a) was found to be significantly associated with K10 scores, or psychological stress ($\beta = 0.2$, $p = 0.01$) after confounder adjustment as shown in Table 11. This is interpreted as an increased K10 score of 0.27 for every 10% increase in distance between a neighbourhood centroid and the nearest green space feature. Proximity to blue space (Model 2b) was not found to have a significant association with K10 scores.

Personal income was significantly associated with K10 scores in Models 2a and 2b, where K10 scores were expected to decrease by 0.9 and 1.02 respectively for each increasing income group ($\beta = -0.09$, $p = 0.01$), ($\beta = -1.02$, $p < 0.001$) (Table 11). Neighbourhood deprivation was positively associated with K10 scores, as found in previous models, although not significantly ($p = 0.1$ and 0.06). Sex, age, population density and crime rates were not significantly associated with K10 scores.

Table 11: Results from two multiple regression models showing the association between 10 percentiles of i) distance to green space and ii) distance to blue space as exposure percentiles and K10 scores (dependent variable) while controlling for selected covariates. K10 values range from 0 – 40 with higher values indicative of increased psychological stress.

Outcome = K10 Score	Model 2a: Proximal distance to green space					Model 2b: Proximal distance to blue space				
Variables	β	SE	P	95% CI		β	SE	P	95% CI	
Proximity to green space	0.20	0.08	<0.001	0.04	0.36					
Proximity to blue space						0.10	0.10	0.33	-0.10	0.31
Sex	-0.59	0.51	0.25	-1.60	0.42	-0.54	0.52	0.30	-1.56	0.48
Age	-0.07	0.08	0.38	-0.24	0.09	-0.06	0.08	0.51	-0.22	0.11
Income	-0.90	0.35	0.01	-1.58	-0.21	-1.02	0.35	<0.001	-1.72	-0.33
NZDep06	0.20	0.12	0.10	-0.04	0.43	0.26	0.14	0.06	-0.01	0.54
Population density	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.13	0.00	0.00
Crime rate	-0.04	0.03	0.25	-0.10	0.02	-0.01	0.03	0.69	-0.08	0.05

No evidence was found to suggest that increased access to quantities of green or blue spaces were significantly associated with K10 scores (Table 12). As in the above models, personal income was significantly associated with K10 scores, where K10 scores decreased by at least 1.04 for each increasing income group in model 3a through to 3c (Table 12). Sex, age, neighbourhood deprivation, population density and crime rates were not significantly associated with the psychological stress outcome.

Table 12: Results from three multiple regression models showing the association between 10 percentiles of i) access to quantities of green space, ii) access to quantities of blue space and iii) access to quantities of all natural environments as exposure percentiles, and K10 scores (dependent variable) while controlling for selected covariates. K10 values range from 0 – 40 with higher values indicative of increased psychological stress.

Outcome = K10 Score	Model 3a: Access to quantities of green space					Model 3b: Access to quantities of blue space					Model 3c: Access to quantities of total natural environments				
Variables	β	SE	P	95% CI		β	SE	P	95% CI		β	SE	P	95% CI	
Quantity of green space	-0.01	0.09	0.87	-0.19	0.16										
Quantity of blue space						-0.06	0.09	0.45	-0.23	0.10					
Quantity of natural environments											-0.05	0.13	0.67	-0.30	0.19
Sex	-0.55	0.52	0.29	-1.57	0.47	-0.52	0.52	0.32	-1.54	0.50	-0.56	0.52	0.28	-1.58	0.45
Age	-0.07	0.09	0.44	-0.24	0.10	-0.05	0.08	0.55	-0.22	0.11	-0.06	0.08	0.46	-0.23	0.10
Income	-1.04	0.35	<0.001	-1.73	-0.34	-1.03	0.35	<0.001	-1.72	-0.34	-1.04	0.35	<0.001	-1.73	-0.34
NZDep06	0.20	0.13	0.11	-0.05	0.45	0.21	0.12	0.09	-0.03	0.45	0.19	0.13	0.15	-0.07	0.45
Population density	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.12	0.00	0.00
Crime rate	-0.03	0.03	0.43	-0.09	0.04	-0.02	0.03	0.55	-0.08	0.04	-0.03	0.04	0.39	-0.11	0.05

Surprisingly, increased proximity to green space was found to have a significant positive association with the physical activity indicator (OR = 1.11, p = 0.02) (Model 4a Table 13). Individuals were found to be 11% more likely to meet recommended physical activity guidelines for every 10% increase in distance from the nearest green space feature, suggesting that people living farther from green spaces tend to be more physically active. Although increased proximity to nearest blue space (Model 4b) had a negative association with the physical activity indicator it was not found to be significant (OR = 0.96, p = 0.45).

Age had an independent, significant association with the physical activity outcome in Models 3a and 3b (OR = 0.84, p < 0.001). This shows that individuals are 16% less likely to meet physical activity guidelines with each increasing age group relative to the youngest group (15-44 years). Higher neighbourhood deprivation was associated with lower physical activity, although only significantly in Model 3b (p = 0.05).

Table 13: Results from two multiple regression models showing the association between 10 percentiles of i) distance to green space and ii) distance to blue space as exposure percentiles and physical activity (dependent variable) while controlling for selected covariates.

Outcome = Physical activity	**Model 4a: Proximal distance to green space**					**Model 4b: Proximal distance to blue space**				
Variables	**OR**	**SE**	**P**	**95% CI**		**OR**	**SE**	**P**	**95% CI**	
Proximity to green space	1.11	0.05	0.02	1.02	1.21					
Proximity to blue space						0.96	0.05	0.45	0.87	1.06
Sex	0.85	0.22	0.53	0.52	1.41	0.89	0.22	0.64	0.54	1.46
Age	0.84	0.04	<0.001	0.77	0.91	0.84	0.04	<0.001	0.77	0.92
Income	0.87	0.15	0.42	0.63	1.21	0.81	0.13	0.21	0.59	1.12
Overweight/obese	1.18	0.32	0.54	0.69	2.00	1.24	0.34	0.43	0.73	2.12
LTHC	1.50	0.40	0.13	0.88	2.53	1.54	0.41	0.11	0.91	2.60
NZDep06	0.90	0.05	0.06	0.80	1.01	0.88	0.06	0.05	0.78	1.00
Population density	1.00	0.00	0.43	1.00	1.00	1.00	0.00	0.19	1.00	1.00
Crime rate	0.97	0.02	0.12	0.94	1.01	0.97	0.02	0.18	0.94	1.01
Air pollution	0.99	0.02	0.66	0.95	1.03	0.99	0.02	0.78	0.95	1.04

Access to quantity of green space (p = 0.71) blue space (p = 0.25) and all natural environments (p = 0.06) were found to have no significant association with physical activity (Table 14). However the proportion of total natural environments within 3km of neighbourhood centroids (Model 5c) was found to have much stronger positive association with the physical activity indicator (OR = 1.10) and was approaching statistical significance (p = 0.06). This suggests that there may be a weak effect for individuals living in neighbourhoods with increased access to both green and blue spaces being more likely to meet physical activity guidelines.

As expected, age was found to be significantly associated with the number of people meeting recommended physical activity guidelines. In Models 5a-5c, individuals were 16% less likely to meet recommended physical activity guidelines with each increasing age group compared to the reference group (15-44 years).

Table 14: Results from three multiple regression models showing the association between 10 percentiles of i) access to quantities of green space, ii) access to quantities of blue space and iii) access to quantities of all natural environments, and physical activity (dependent variable) while controlling for selected covariates.

Outcome = Physical activity	Model 5a: Access to quantities of green space					Model 5b: Access to quantities of blue space					Model 5c: Access to quantities of total natural environments				
Variables	OR	SE	P	95% CI		OR	SE	P	95% CI		OR	SE	P	95% CI	
Quantity of green space	0.97	0.04	0.54	0.89	1.06										
Quantity of blue space						1.02	0.05	0.67	0.93	1.11					
Quantity of natural environments											1.10	0.06	0.09	0.99	1.22
Sex	0.88	0.22	0.61	0.53	1.44	0.88	0.22	0.63	0.54	1.45	0.92	0.23	0.74	0.56	1.51
Age	0.84	0.04	0.00	0.77	0.92	0.84	0.04	0.00	0.77	0.92	0.84	0.04	0.00	0.77	0.92
Income	0.82	0.13	0.21	0.59	1.13	0.82	0.13	0.21	0.59	1.12	0.81	0.13	0.21	0.59	1.13
Overweight/obese	1.23	0.33	0.45	0.72	2.09	1.23	0.33	0.44	0.73	2.09	1.22	0.33	0.46	0.72	2.09
LTHC	1.54	0.41	0.11	0.91	2.61	1.54	0.41	0.11	0.91	2.61	1.48	0.40	0.15	0.87	2.51
NZDep06	0.90	0.05	0.07	0.80	1.01	0.90	0.05	0.08	0.80	1.01	0.93	0.06	0.22	0.82	1.05
Population density	1.00	0.00	0.22	1.00	1.00	1.00	0.00	0.21	1.00	1.00	1.00	0.00	0.07	1.00	1.00
Crime rate	0.98	0.02	0.21	0.94	1.01	0.98	0.02	0.22	0.94	1.01	0.99	0.02	0.79	0.95	1.04
Air pollution	0.99	0.02	0.78	0.95	1.04	0.99	0.02	0.79	0.95	1.04	0.99	0.02	0.69	0.95	1.03

6.8 Research Question 3: Is increased physical activity associated with decreased psychological stress?

6.8.1 Bivariate analysis

Very little evidence was found to support the notion that physical activity was associated with psychological stress in the study population. Individuals meeting recommended physical activity guidelines were found to have a slightly lower average K10 scores (5.2 for regularly active individuals and 6 for non-regularly active individuals), indicating slightly improved psychological well-being over individuals who did not meet recommended physical activity guidelines.

6.8.2 Results of regression models

Whether an individual met recommended physical activity guidelines or not was not found to be significantly associated with K10 scores ($\beta = 0.66$, $p = 0.18$) (Model 6a, Table 15). Income was found to be significantly, negatively associated with activity ($\beta = -0.97$, $p < 0.001$) suggesting that increasing age groups experience less stress. Long-term health conditions were positively associated with increased K10 scores ($\beta = 1.86$, $p < 0.001$). In other words, individuals with a long term health condition were expected to have a K10 score increase of 1.86 compared with those with no long term health conditions.

Table 15: Multiple regression analysis for physical activity (independent variable) and psychological stress (dependent variable).

Outcome = K10 Score	**Model 6a: Indicator of physical activiy**				
Variables	**β**	**SE**	**P**	**95% CI**	
Physically active (yes/no)	0.66	0.49	0.18	-0.31	1.63
Sex	-0.36	0.49	0.46	-1.32	0.60
Age	-0.14	0.09	0.12	-0.31	0.03
Income	-0.97	0.33	<0.001	-1.63	-0.31
LTHC	1.86	0.50	<0.001	0.86	2.85
Overweight/obese	-0.01	0.53	0.98	-1.05	1.02
NZDep06	0.26	0.12	0.03	0.02	0.49
Population density	0.00	0.00	0.07	0.00	0.00
Crime rate	-0.01	0.04	0.79	-0.08	0.06
Air pollution	0.03	0.04	0.45	-0.05	0.11

Chapter 7: Discussion

7.1 Summary of findings, interpretation, and comparisons with existing literature

The relationship between natural environments and health have become of increased interest as an increasing body of research finds links between exposure to natural environments and improved mental health in urban settings. However, to date, the majority of research has focused specifically on urban green space and health outcomes and does not include other natural environments such as blue space. Furthermore, studies rarely seek to explore the separate theoretical causal pathways through which benefits of natural environments may improve health. Such research is important to increase the understanding of this field in order to take advantage of direct and indirect benefits of green and blue spaces such as increases in physical activity with the end goal of reducing the mental health burden for populations.

7.1.1 Visibility and psychological health

Increased visibility of natural environments was associated with lower psychological stress. Increased visibility of blue space had the strongest influence on psychological stress reduction while controlling for confounders, suggested that residents living in neighbourhoods with increased views of blue space have lower stress levels. The finding that being able to see blue space improves mental wellbeing is in accordance with a number of studies that use qualitative methods, such as photographical response analysis, to demonstrate that visibility of waterscapes strongly induces positive perceptions (Herzog, 1985; Ulrich, 1981; Völker & Kistemann, 2011; White et al., 2010). This study observed visible blue space to have the greatest association with stress reduction, a notion that is supported by Ulrich (1981) and White et al. (2013b) who found scenes of blue space may have a stronger influence on mental health than views of green space. Furthermore, Richardson et al. (2010) offers theoretical support that blue space may be of more significance in New Zealand than green space due to the countries island geography. Finally, it is possible that blue space is simply a better representation of natural environments than green space, especially in urban settings where sports fields and open parks fall under the category of 'green nature'. This would suggest that the salutogenic or therapeutic effect of blue space is stronger than green space.

Still, it is possible that associations between visibility of blue spaces and decreased psychological stress were reduced due to the proximity of Wellington city (particularly the CBD) to the coast. Although some individuals may not be living in neighbourhoods with views of blue space, it is likely that through the course of a normal day, they will come into visual contact with it (i.e. driving to/from work). For this reason, this study was unable to make comparisons between individuals with long-term exposure to blue space against individuals who rarely saw blue space. Rather it is likely to be comparing individuals with long-term exposure (i.e. from a home address) vs. individuals who see it for a short time on a regular basis. This effect would reduce the impact that observing blue space scenes would have between the two groups.

In terms of green space and mental health, it was found that increased visible green space beyond 3km was associated with decreased psychological stress, whereas this association disappeared at nearer distances. Total visible green space irrespective of distance from the observer was not found to have a statistically significant association with psychological stress which suggests that the spatial distribution of green space relative to a viewer may be more important than the quantity. Importantly, these findings also indicate that more distant natural green areas may be more influential to improved mental health than nearby greenery. There are a number of possible explanations for this finding. Firstly, greenery beyond 3km is likely to be consistently visible to an individual as they move about their local neighbourhood and therefore represent consistent exposure to green space. Secondly, Wellington City has a significant presence of greenery in background gardens which were not included in measures of green space. It is possible that residents across the city are exposed to a similar base level of greenery within their immediate neighbourhood, while views of distant green spaces vary more. This is reflected in the standard deviation values for measures of green space within 300m and between 6km & 15km (452 and 743 respectively). It is also possible that too much localised green space may be intrusive, create a crowded effect and reduce light and airflow, as suggested in other research (Kuo, Bacaicoa, & Sullivan, 1998). Increased vegetation within short distances has also been found to increase the sense of fear (Rachel Kaplan & Talbot, 1988; Kuo et al., 1998) which is known to not be associated with crime rates in New Zealand (Pearson & Breetzke, 2013).

Still, this finding stands in contrast to a number of other qualitative studies. For example, Moore (1981) found a stress reduction for prisoners with green views immediately out the window compared to prisoners with courtyard views. Similarly, other studies found positive associations between nature visibility out a window and mental health (R. Kaplan, 2001; Kearney, 2006). These findings however are all qualitative and based on individual views and do not necessarily reflect the neighbourhood or area level visibility of green space. Additionally, the majority of these qualitative studies took place in heavily urbanised areas where those without visible green space often had unsightly and predominantly non-natural views (i.e. building facades prison courtyards, and infrastructure). Therefore, contrasting these views with those involving green areas may have led to the observed relationship with improved mental health. In Wellington's highly undulating environment and proximity to the coast, there is potential for many neighbourhoods to have wide open views of blue space and distant greenery (for example looking from the hills behind the Wellington City centre across the harbour to the Rimutaka Range). These views may be perceived as more aesthetic than nearby vegetation, and thus partially explain the association found between increased visibility of distant green space and improved mental health.

The visibility of total natural environments was also found to have a significant association with psychological stress after adjusting for confounders suggesting that increased views of green and blue spaces reduce levels of stress. The relationship between visibility of all natural environments and stress was observed to be slightly weaker than for blue space. This is an interesting find and conflicts with a number of studies. White et al. (2010) used photographical response analysis to find that the most preferred views of natural environments consisted of two-thirds blue space while Völker & Kistemann (2011) suggest that diversity, edges and borderlines between aquatic environments and land are also important characteristics of aesthetic scenes.

7.1.2 Access to natural environments and health outcomes

A large assumption in many studies investigating the influence of natural environments, particularly green space, and health is that increased measures of access are associated with an increase in their use, thereby encouraging physical activity, social interaction and exposure to relaxing environments, all which are thought to contribute improvements in mental health (Nutsford et al., 2013; Richardson et al., 2010, 2013). This section is broken into two parts. The first investigates the relationship between measures of access to natural environments and psychological stress while the second examines physical activity a possible mechanism.

7.1.2.1 *Access to natural environments and psychological stress*

Increased proximal access to green space was associated with lower psychological stress. This finding is consistent with a recent study by Stigsdotter et al. (2010), which found that people living less than 300m from a green space reported better mental health than people living farther away. Similarly, in New Zealand, Nutsford et al. (2013) found that areas with better proximal access to useable green spaces were associated with lower levels of anxiety/mood disorders.

In terms of blue space, increased access to blue space was not associated with lower stress. In contrast, Völker & Kistemann (2011) concluded in a recent review that a strong body of evidence suggests that blue space has numerous mental wellbeing benefits, both through access and visibility. In line with this conclusion, quantitative studies find increased access to the coast to be associated with improved mental health (Wheeler et al., 2012; White et al., 2013a). One possible reason for the findings of this study opposing those from all other identified quantitative studies investigating the association between access to blue space and mental health could include the measure of access to blue space, which failed to represent popular areas for accessing water such as beaches or wharfs. Rather it used the closest area of blue space, which was unlikely to represent direct access to recreational areas near blue space.

When conceptualising access in terms of quantities of green space, blue space or all natural environments, no associations were observed with psychological stress. While this finding is consistent with studies conducted elsewhere (Annerstedt et al., 2012; Nielsen & Hansen, 2007), it does contrast with other studies conducted in New Zealand investigating green space access and mental health (Nutsford et al., 2013; Richardson et al., 2013). Here, possible explanations for these findings are offered. Firstly, New Zealand is known for its clean, green image and reduced variation in access to green space in comparison to other global cities may make the detection of a significant association difficult. Richardson et al.

(2010) noted that New Zealand's main urban areas have average green space coverage of 42%, a coverage that is notably higher than urban areas used in most European studies. This is reinforced by Witten et al. (2008) who suggested that the "vast majority of New Zealanders have good access to a park, rendering it a non-discriminatory predictor of health" (p. 302). Secondly, it is likely that areas with large quantities of green space are also more peripheral urban environments, which may be more isolated. Isolation has been identified as a factor linked to increased anxiety and stress in New Zealand (Mental Health Commission, 2012; Ministry of Social Development, 2010).

7.1.2.2 *Access to natural environments and physical activity*

No evidence was found that suggests increased access to green spaces, blue spaces, or total natural environments were associated with physical activity. In fact, surprisingly, individuals living in neighbourhoods nearer to green spaces were less likely to meet recommended physical activity guidelines compared to those living in areas farther from green spaces. Results from other studies on the relationship between access to green space and physical activity have been mixed. Ellaway, Macintyre, & Bonnefoy (2005), for example, found that residents living in neighbourhoods with high levels of greenery were three times more likely to be physically active and 40% less likely to be overweight or obese in eight European countries. Giles-Corti et al. (2005) found that distance, attractiveness and size of open public space all influenced levels of physical exercise and people with good access to green space were found to be 50% more likely to be physically active. In New Zealand, E. A. Richardson et al., (2013) observed that individuals living in greener neighbourhoods were more likely to meet recommended physical activity guidelines. On the other hand, and similar to the findings of this study, other studies conducted have found no relationship or a negative relationship between access measures to green spaces and physical activity (Foster et al., 2009; Hillsdon et al., 2006; Maas et al., 2008). Importantly, the majority of studies conducted in New Zealand support findings of this study. Witten et al., (2008) found no association between green space access and BMI or individual level physical activity while Richardson et al. (2010) found no relation between access to green spaces and cardio-vascular disease, which in turn is strongly correlated with physical inactivity. Reasons for negative associations could be that physical activity (especially transport-related) could be higher in built-up environments without green space, as found in the Netherlands (Maas et al., 2008). Other speculative reasons for negative findings include that this study did not account for a number of important factors which may have influenced the association between access to nature and physical activity. In 2004, a review of 18 studies found that aesthetic factors such as trees, grassy verges, green backyards and diverse views encourage physical activity. It also identified a number of determinants such as convenience facilities (footpaths, trails), level of road traffic and target destinations (shops, public amenities etc.) (Owen, Humpel, Leslie, Bauman, & Sallis, 2004). Not including these factors as covariates may have influenced the observed findings.

In addition, in Wellington City, a decrease in access to green space may be related to an increase in access to fitness facilities such as gyms and recreational centres (nearer the city centre), which may be desirable places for physical exercise, particularly in urban settings. It is also possible that areas with increased green space tend to have facilities such as shops and social hubs located farther away, promoting the use of non-active means of travel such as private vehicles or public transport over walking or cycling. Furthermore, greener neighbourhoods tend to be spaciously arranged, have less traffic and increased parking opportunities and vehicle access, which would further encourage the use of private motor vehicles (Maas et al., 2008). Conversely, studies have found that people are more likely to walk or cycle as means of transportation in neighbourhoods with a high density of facilities, where private parking is limited and there is increased traffic (Foster et al., 2009; Maas et al., 2008). Finally, there are a few characteristics unique to Wellington City which may influence the active behaviour of individuals. While the CBD itself is flat (and less green), residential areas of Wellington are highly undulated (and green). These factors may dissuade physical activity in greener areas and encourage it promote physical activity in the less green areas.

Finally, this study only accounted for individuals who meet recommended physical activity guidelines and did not represent individuals who were partaking in moderate to low levels of activity. As such, results indicate that increased access to natural environments is not associated with regular active individuals, however it may be encouraging more moderate levels of activity from individuals who would otherwise exercise less.

7.1.3 Physical activity and psychological stress

It is often thought that engaging in physical activity in natural environments has numerous health benefits – including mental health benefits. As such, the relationship between measures of physical activity and psychological stress was investigated, but no significant associations were found. These findings are unexpected as the majority of studies have found physical activity to be associated with reduced psychological stress, anxiety and other indicators of mental illness (Barton & Pretty, 2010; Fontaine, 2000; Nielsen & Hansen, 2007; Richardson et al., 2013; Tenenbaum & Eklund, 2007). There are a number of potential reasons why no association was observed between physical activities and reduced psychological stress in this study. Firstly, studies have found physical activity to be associated with improved mental health only when it is conducted in leisure-time as opposed to workplace activity (which includes commuting to work) (Harvey, Hotopf, Overland, & Mykletun, 2010). In may be difficult for individuals, particularly those working full time and/or with families to meet the recommended physically active guidelines of 30 minutes of exercise, 5 days or more a week, within *leisure-time.* Therefore the 'active' individuals of the study population may have comprised of adults meeting the physical activity guidelines outside of "leisure-time" hours, for example at work, in which case a decrease in psychological stress would not be expected.

Importantly, this study did not include data on where physical activity was taking place, therefore it was not possible to identify links between exercise *within* natural environments and health outcomes. It is possible that individuals exercising less but *within* green spaces are receiving added health benefits compared to individuals exercising more frequently but *outside of* green spaces. Pretty et al. (2005) conducted a study which investigated the influence of exposure to nature while running on a treadmill, and found that participants exposed to pleasant rural and urban scenes while exercising had improved measures of blood-pressure, self-esteem and mood over the control group. While exercise for the control group still improved measures of blood pressure and mood, these were drastically reduced amongst participants who were exposed to images of non-pleasant rural and urban scenes. Similarly, a review conducted in 2011 by Thompson Coon et al. (2011) found that self-reported well-being was typically higher after outdoor exercise in comparison to indoor exercise in a numerous studies. Social exercise is also known to be more conducive for promoting mental health, especially among women (Ball, Bauman, Leslie, & Owen, 2001). These findings suggest that perhaps the location and potential social elements of exercise may be as important to mental health as the quantity. Still, regardless of the location of physical activity, these results warrant further exploration.

7.2 Limitations, strengths and ways forward

7.2.1 Study limitations

This study is not without its limitations and it is important to note that there are future improvements that could be made. Perhaps the biggest limitation with this study is its multi-level study design, and therefore causal inference is not possible(Francis et al., 2012; MacKerron & Mourato, 2013; de Jong et al., 2012). For example, it is unknown whether people who have good mental health choose to live in areas with lots of greenery or whether they have good mental health due to positive effect of green environments. In addition, the data used to represent exposure to natural environments was derived from large scale public data sources which classified areas with varying degrees of attribute information and contiguity. The resulting dataset was an accurate spatial representation of public green areas and large homogenous land parcels (such as farm land) and coastal and in-land water bodies, but did not include private green spaces such as backyard gardens, which have been found to be important for stress reduction (Stigsdotter & Grahn, 2004). Incorporating private backyards and small scale green areas also would have allowed us to create and index of streetscape quality which has been shown to encourage physical exercise (Maas et al., 2008). Due to a negligible influence of inland blue space (rivers, lakes) this study was unable to accurately investigate whether inland blue spaces offer any benefits independent of coastal blue environments. While studies have found associations between positive moods and inland blue spaces, such as Völker & Kistemann (2013) who identified health promoting aspects of the river Rhine in two German cities, it is yet to be examined using a quantitative approach. Other studies also recognize this limitation (White et al., 2013a) and further work is needed to explore the spatial distribution of lakes and rivers relative to people and their mental health.

Next, there are a few limitations related to data used. Visibility and access measures did not include quality aspects such as cleanliness due to the incomplete, imprecise and lack of attribute information pertaining to green spaces and the subjective nature of these factors. Studies have found that certain characteristics of green spaces encourage use while others dissuade it, specifically, quality and size (Francis et al., 2012; Hofmann, Strobl, & Nazarkulova, 2011). Size of green space was also an important characteristic of green space which was not accounted for. As another data limitation, the measure of neighbourhood socio-economic deprivation was derived from the 2006 census however, the health data were obtained in 2011/12, however one study found that relative neighbourhood deprivation remains similar for most areas within this time frame (Pearson, Apparicio, & Riva, 2013). Moreover, the lag could potentially be useful in terms of a lag time effect between exposure to characteristics typical of deprived neighbourhoods and mental health outcomes (Pearson et al., 2012). As required for maintaining confidentiality, this study did not make use of home locations of study participants for the generation of exposures to natural environments, rather it used the population-weighted centroid of their home MB (average size of 0.1km^2). While this is commonplace in health geography studies to maintain ethical standards, it represents a significant decrease in the accuracy of findings and the use of these centroids introduces a lack of precision in spatial measures for individuals. Likewise, age and personal income for respondents were provided as ordered categorical data in order to comply with ethical standards. This represents a further loss of precision. Additionally, this study did not account for the length of residence in a neighbourhood and the outcome. It is assumed that any influences of natural environments on mental health and well-being are not instantaneous and that an individual must be exposed to them for a period of time before any benefits can be derived. Finally, the study only accounted for the visibility of natural environments from neighbourhoods where individuals lived and was unable to account for exposure at work or when travelling. As such this work only investigates the influence of long-term exposure to natural environments.

Finally, the binary variable used in the study to indicate whether an individual was physically active or not was generated from a number of questions about levels of activity within the last seven days. There is likely to be some weather and seasonal variation in this response. The health survey was conducted over the course of one year with approximately 25% of data collected every quarter, which should minimise this source of bias unless data for parts of Wellington were collected in only two quarters, for example.

7.2.2 Study strengths

This study overcame several limitations found in previous studies. It is one if the few studies that incorporates accurate measures of both green and blue space and the first study internationally to use a quantitative measure of natural environments visibility and link it to a health outcome. While some other studies have used qualitative measures, such as photographical response analysis (White et al., 2010) and surveys (Velarde et al., 2007) to assess positive effects of aesthetic environments, this is the first identifiable study to find that increased visible blue and green space improves metal wellbeing based on a quantitative study design. Incorporating both green and blue spaces overcomes many limitations of studies which ignore blue space or treat it as a component of green space. It allowed us to independently assess benefits of green space, blue space and combined measures on mental health which is especially important due to the coastal distribution of New Zealand's population.

Due to a large number of individual and area-level covariates this study was able to control for factors that influence exposure to natural environments, mental health or both. Failing to control for confounding factors is recognised to introduce uncertainty into the findings of regression models (Tzoulas et al., 2007). A typical limitation of epidemiological studies is the prevalence of 'missing data' and their potential to undermine the validity of results (Sterne et al., 2009). This study used multiple imputations, a statistical method that predicts values of missing data based on the values of obtained data to interpolate missing values for BMI and income, which allowed us to make use of the full study population.

Finally, this study used accurate GIS techniques to create access and visual exposure variables to natural environments. The visibility index adjusted for the vertical significance of terrain and represents visibility from the human perspective, an improvement over the standard viewshed process. Proximal access was created to reflect travel distance through a road network which overcomes limitations of Euclidean distance measures and is in line with recommendations from Higgs et al. (2012) who conducted a study on different GIS techniques used to measure green space accessibility. Access to quantity is a popular technique used in many studies and is recognised as an accurate representation of neighbourhood exposure to natural environments (Maas et al., 2009, 2006; Nutsford et al., 2013; van den Berg et al., 2010).

7.2.3 Directions for future research

Future improvements include a longitudinal study design which would allow more accurate representations of exposure to natural environments and allow direct correlations at the individual level. This research would also benefit from more detailed health questions, particularly the indicator of physical activity which fails to account for individuals who undertook moderate levels of physical activity. Including additional health outcomes would be of further benefit and further increase an understanding of health and the natural environment.

Automated satellite image classification techniques could be used as a method to incorporate private and backyard green spaces as well as measures of streetscape and the techniques are already in place (De Ridder et al., 2004; Miller et al., 2009; Taylor et al., 2011). Finally, by repeating the study in an area with varied exposure variables to useable and other green space would be more appropriate for investigating whether specifically access to useable green spaces promote activity and health.

7.3 **Potential research implications**

This research is important in a number of ways and provides a base to inform the direction of urban planning and health promotion decisions. A first impression of these findings could be that the influence of natural environments on mental health in urban settings of New Zealand may be less of a priority as seen in other countries. While this study, and the work conducted by Nutsford et al. (2013) found significant associations between increased exposure to natural environments and positive mental health outcomes, the effect sizes were relatively small. Nonetheless, and although some of the findings were in conflict, it appears that natural environments may affect indicators of mental health, and creative urban design may contribute to reductions in the mental health burden. The visibility of natural environments appears to be more important in regards to stress reduction than accessibility, and should become a focus for mental health promotion. Specifically, the finding that visible distant green space and visible blue space promotes mental health and stress reduction has important implications for urban design. While establishing green spaces within urban settings have been a recommended focus for reducing the mental health burden globally (WHO, 2006), the findings of this study suggest a shift in focus to promoting distant greenscapes which may or may not be outside of the city limits. For example 'greenifying' prominent visual areas such as hillsides and elevated areas may be more beneficial to a greater number of residents than smaller, localised green areas. Green space within close proximity was not found to have a positive association with mental health, and in fact model results indicated a non-significant negative association.

Conclusion

This study investigated whether natural environments had an influence on mental health and physical activity in Wellington City, New Zealand. Green spaces such as parks, gardens, school yards, sports fields, protected spaces (e.g. riparian zones) and recreational forests (Cicea & Pîrlogea, 2011) and blue spaces or natural dynamic or static water bodies such as rivers, lakes and oceans, are two broad categories of natural environments which have been associated with positive health outcomes (Francis et al., 2012; Maas et al., 2009; de Jong et al., 2012; van den Berg et al., 2010). Specifically, this study investigated whether increased visibility and access to blue and green space decreased psychological stress and increased physical activity. While many quantitative studies exist that associate increased access to natural environments with improved health, this is the first study internationally to take a quantitative approach to measuring visibility of green and blue space and link it to health outcomes.

Results indicated that increased views of natural environments, particularly blue space and distant green space were associated with decreased psychological stress while controlling for confounding factors. While increased proximal access to green space was associated with decreased stress other measures of access to natural environments were not found to influence stress. We found no evidence to suggest increased access to natural environments increased physical activity. In fact, residents living in neighbourhoods close to green space were less likely to meet recommended physical activity guidelines compared to residents living farther away.

These results indicate that perhaps increased visibility of natural environments is more important in terms of stress reduction than increased access. Through this notion, the therapeutic or background effect of nature may be a stronger mechanism leading to improved mental health than physical activity. This finding has strong policy implications and creative urban design should be used to maximise the visibility of nature in urban environments, particularly blue space and distant greenery which may or may not be outside of the city limits.

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Appendices

Appendix A: Supporting Data

The Kessler Psychological Distress Scale (K10) Questionnaire

1) During the last 30 days, about how often did you feel tired out for no good reason?
2) During the last 30 days, about how often did you feel nervous?
3) During the last 30 days, about how often did you feel so nervous that nothing could calm you down?
4) During the last 30 days, about how often did you feel hopeless?
5) During the last 30 days, about how often did you feel restless or fidgety?
6) During the last 30 days, about how often did you feel so restless you could not sit still?
7) During the last 30 days, about how often did you feel depressed?
8) During the last 30 days, about how often did you feel that everything was an effort?
9) During the last 30 days, about how often did you feel so sad that nothing could cheer you up?
10) During the last 30 days, about how often did you feel worthless?

The response to each question is recoded as follows: 'all of the time' = 4; 'most of the time' = 3; 'some of the time' = 2; 'a little of the time' = 1; 'none of the time' = 0 and all other values set to missing. This gives a possible range of scores between 0 and 40 (Oakley Browne et al., 2010)

Formulation of the binary indicator for physical activity

A binary indicator for physical activity was derived from three questions posed in NZHS:

i) *In the last seven days, how many minutes did you spent briskly walking?*

ii) *In the last seven days, how many minutes did you spend doing moderate physical activities?*

iii) *In the last seven days, how many minutes did you spend doing vigorous physical activities?*

Responses to these questions were used to infer whether a respondent was meeting the recommended physical activity guidelines of at least 30 minutes of exercise on 5 or more days a week.

Complete list of created exposure variables

Visual exposure variables	**Included in Statistical Analysis**
Visible green space (high quality)	No
Visible green space (medium quality)	No
Visible green space (low quality)	No
Visible green space (high quality)	No
Total visible natural environments (high quality)	No
Total visible natural environments (medium quality)	No
Total visible natural environments (low quality)	No
Total visible green space	Yes
Visible green space < 300m	Yes
Visible green space between 300m & 3km	Yes
Visible green space between 3km & 6km	Yes
Visible green space between 6km & 15km	Yes
Total visible blue space	Yes
Visible blue space < 300m	No
Visible blue space between 300m & 3km	No
Visible blue space between 3km & 6km	No
Visible blue space between 6km & 15km	No
Total visible natural environments	Yes
Visible natural environments < 300m	No
Visible natural environments between 300m & 3km	No
Visible natural environments between 3km & 6km	No

Visible natural environments between 6km & 15km	No
Proximal Access	
Distance to nearest green space	Yes
Distance to nearest useable green space	No
Distance to nearest blue space	Yes
Distance to nearest natural environment	Yes
Distance to nearest useable natural environment	No
Access to Quantity	
Proportion of green space within 3km of neighbourhood centroid	Yes
Proportion of useable green space within 3km of neighbourhood centroid	No
Proportion of blue space within 3km of neighbourhood centroid	Yes
Proportion of natural environments within 3km of neighbourhood centroid	Yes
Proportion of useable natural environments within 3km of neighbourhood centroid	No

Appendix B: Supporting tables

A comparison between estimates produced with a restricted complete dataset (n=315) and estimates produced with the dataset that replaced missing values with imputed values (n=442)

	Non-Imputed Dataset					Imputed Dataset				
Outcome: K10	**β**	**SE**	**P**	**95% CI**		**β**	**SE**	**P**	**95% CI**	
Visible Blue Space	-0.35	0.07	<0.001	-0.48	-0.22	-0.32	0.07	<0.001	-0.45	-0.19
Sex	-0.49	0.56	0.38	-1.59	0.61	-0.42	0.50	0.40	-1.40	0.56
Age	-0.08	0.09	0.39	-0.25	0.10	-0.04	0.08	0.60	-0.20	0.12
Income	-0.78	0.30	0.01	-1.38	-0.19	-0.90	0.33	0.01	-1.56	-0.25
NZDep06	0.20	0.13	0.13	-0.05	0.45	0.23	0.12	0.05	0.00	0.47
Population Density	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.04	0.00	0.00
Crime Rate	0.00	0.03	0.87	-0.06	0.05	-0.01	0.03	0.76	-0.06	0.05
Outcome: K10	**β**	**SE**	**P**	**95% CI**		**β**	**SE**	**P**	**95% CI**	
Distance to green space	0.17	0.09	0.05	0.00	0.35	0.20	0.08	0.01	0.04	0.36
Sex	-0.70	0.58	0.23	-1.85	0.45	-0.59	0.51	0.25	-1.60	0.42
Age	-0.10	0.09	0.26	-0.28	0.08	-0.07	0.08	0.38	-0.24	0.09
Income	-0.83	0.32	0.01	-1.46	-0.20	-0.90	0.35	0.01	-1.58	-0.21
NZDep06	0.18	0.13	0.17	-0.08	0.44	0.20	0.12	0.10	-0.04	0.43
Population density	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.05	0.00	0.00
Crime rate	-0.03	0.03	0.38	-0.09	0.04	-0.04	0.03	0.25	-0.10	0.02
Outcome: Physical activity	**OR**	**SE**	**P**	**95% CI**		**OR**	**SE**	**P**	**95% CI**	
Quantity of natural environments	1.16	0.07	0.02	1.03	1.32	1.10	0.06	0.09	0.99	1.22
Sex	0.82	0.24	0.49	0.45	1.46	0.92	0.23	0.74	0.56	1.51
Age	0.85	0.04	<0.001	0.77	0.94	0.84	0.04	<0.001	0.77	0.92
Income	0.82	0.14	0.26	0.59	1.16	0.81	0.13	0.21	0.59	1.13
Overweight/Obese	1.15	0.35	0.65	0.63	2.10	1.22	0.33	0.46	0.72	2.09
LTHC	1.41	0.44	0.28	0.76	2.61	1.48	0.40	0.15	0.87	2.51
NZDep06	0.94	0.07	0.42	0.81	1.09	0.93	0.06	0.22	0.82	1.05
Population Density	1.00	0.00	0.11	1.00	1.00	1.00	0.00	0.07	1.00	1.00
Crime Rate	1.00	0.02	0.88	0.96	1.05	0.99	0.02	0.79	0.95	1.04
Air Pollution	1.00	0.02	0.93	0.95	1.05	0.99	0.02	0.69	0.95	1.03