Contextual Factors Explaining Geographical Heterogeneity in Wellbeing: The Role of Climate, Environment, Social Capital, and Residential Mobility

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Abstract

Good policy making will strive to improve human wellbeing. While economics has traditionally focused on the maximisation of utility to achieve this objective, there is now a growing trend to investigate the various factors that determine *subjective* wellbeing. Wellbeing research in the discipline of economics (with a focus on subjective wellbeing) is now a vibrant field of study supported by a solid body of empirical literature. One of the important outcomes from this research is that people are apparently happier in some geographical locations than in others. The aim of this thesis is to investigate the reasons behind the geographic diversity in life satisfaction (LS), the most used metric of subjective wellbeing. From this general objective, I derive broad research questions which I address in the four studies that form the body of research in this thesis. Firstly, does the relationship between LS contributing factors and LS change with geographic location? Secondly, are there interactions between individual factors and contextual factors that contribute to LS? Thirdly, is the impact of contextual factors on LS shaped by individual perception? Fourthly, what is the role of individual mobility in explaining geographic clustering of LS scores?

The data analysed to answer these questions is sourced from Australia, primarily through the Household Income and Labour Dynamics (HILDA) annual surveys and subsidiarily through a custom survey designed to collect individual perceptions about the local climate and the local environment. In the first study, I use Geographically Weighted Regression and determine that climate variables affect individual LS differently in different climatic regions when controlling for individual factors. While higher temperatures and low precipitation have a negative impact on LS for people living in a hot climate zone, the same attributes are associated with higher LS levels in temperate regions with more benign conditions. In the second study, multi-level modelling analysis allows me to establish that, at individual level, social capital factors such as social trust, community engagement, psychological sense of community are positive contributors of LS in urban neighbourhoods. This positive influence is offset by the negative impact of perception about crime and shabbiness in the neighbourhood. Social capital factors at contextual level have a more limited influence except for aggregate community engagement in the neighbourhood which contributes to higher LS levels. The third study is an exploratory study where I develop a multi-stage regression model to analyse custom designed survey data. The outcome from this analysis indicates that satisfaction with the local climate and the local environment are both

positively associated with higher individual LS. The influence of objective climate conditions on the cognitive evaluation of the local climate is shaped by individual perceptions of these conditions and mitigated by the belief that the climate is healthy. Similarly, the positive evaluation of the local climate is associated with a perception of wellbeing benefits derived from the enjoyment of environmental amenities in the local area. In the fourth study, panel data compiled for the period 2013-2021 is analysed to examine the possible role of selective mobility and social influence on LS. I find that residents who report lower LS levels before moving are more likely to move from the city to a rural area or to move to a region with a different climate. When people move from the city to a rural area, the move is associated with an uplift in the individual's LS trajectory over time. A similar uplift is associated with a move from a temperate or cool region to a region with a warmer climate.

The findings from this research contribute to the existing knowledge in wellbeing economics in multiple ways. Firstly, they confirm the importance of contextual factors in shaping individual wellbeing and reveal that these contextual factors, whether they are linked to the natural environment or the socio-economic environment influence people's wellbeing differently at different places. This diversity contributes to heterogeneity in the spatial distribution of LS scores. Secondly, they reveal a degree of interaction between individual social capital factors and corresponding contextual factors that influence individual LS. in urban settings Thirdly, the preliminary findings from my exploratory study suggest that individual subjective perceptions of local environmental conditions often mitigate the influence of these objective contextual factors on LS. Fourthly they highlight the importance of compositional factors linked to diverse individual characteristics in explaining geographical diversity in LS scores.

While my research was conducted within an Australian context, the findings have significance and potential policy making implications beyond Australia. The negative impact of high temperatures is particularly relevant if the climate is to become hotter. This will guide and inform adaptation strategies, particularly in hot and arid climates. Findings about the importance of social capital informs social policy in urban neighbourhoods, in particular the importance of social inclusion and the remedying of social ills such as crime to reinforce the feeling of personal safety. Evidence that a positive perception about the local climate and local environmental amenities is associated with improved wellbeing will help develop policies that promote the health benefits derived from the enjoyment of these amenities. The

reported association between LS levels and selective mobility may help with projections of future population movements and assist in promoting living in regional areas.

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List of acronyms

ABS	Australian Bureau of Statistics
AIC	Akaike Information Criteria (Statistics)
ASGS	Australian Statistical Geography Standard
BEMAS	Business, Economics, Management, and Sustainability
BLI	Better Life Index
BLUE	Best Linear Unbiased Estimator (Statistics)
BOM	(Australian) Bureau of Meteorology
CCD	Census Collection District
CDM	Cooling Degree Months
CSIRO	Commonwealth Scientific and Industrial Research Organisation (Australia)
DV	Dependent variable (Statistics)
EU	European Union
FE	Fixed Effect (estimator) (Statistics)
GDP	Gross Domestic Product
GIS	Geographical Information System
GPI	Genuine Progress Index
GS	Genuine Savings
GWR	Geographically Weighted Regression
HDI	Human Development Index
HDM	Heating Degree Months
HILDA	Household Income and Labour Dynamics in Australia (Survey)
HPI	Happy Planet Index
ICC	Intraclass Correlation Coefficient (Statistics)
ISEW	Index of Sustainable Economic Welfare
IV	Independent Variable (Statistics)
LOTE	Language Other Than English
LS	Life Satisfaction
LSSD	Life Satisfaction Standard Deviation (for an area)
MEA	Millenium Ecosystem Assessment
MLM	Multi-Level Modelling
NDVI	Normalised Difference Vegetation Index
NSW	New South Wales (Australia)
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Square (Statistics)
PCA	Principal Component Analysis (Statistics)
RE	Random Effect (estimator) (Statistics)
SA1	Statistical Area Level 1 (Australia)
SA2	Statistical Area Level 2 (Australia)
SA3	Statistical Area Level 3 (Australia)
SA4	Statistical Area Level 4 (Australia)
SEIFA	Socio-Economic Indexes for Area (Australia)
SWB	Subjective Wellbeing
UK	United Kingdom
US	United States
WA	Western Australia

Publications during PhD

Articles directly related to PhD

Already published (first author)

Lignier P., Jarvis D., Grainger D., Chaiechi T., 2022, 'Geography, Climate and Life Satisfaction' in *Community Empowerment, Sustainable Cities, Transformative economies,* Chaiechi T., Wood J. (eds), Springer, p 451-473

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Chapter 1 Introduction

In this chapter I outline the background and objectives of this thesis and provide a rationale for my research.

1.1 General Introduction

There appears to be a broad consensus among politicians, policy makers and academics that good policy making is fundamentally important to improving people's wellbeing, nonetheless a divergence exists about what is the best way to achieve this goal. The current orthodoxy of economics adheres to the idea that improving human wellbeing is synonymous with maximising utility, while a growing chorus of dissenting voices call for more attention to be paid to *subjective* wellbeing.

Firstly, good policy that seeks to improve human wellbeing requires an understanding of both what is meant by wellbeing and how to measure it. Secondly, designing effective and appropriate policy to improve wellbeing demands that policymakers have a good understanding of what economic, social, cultural and environmental factors most significantly impact on wellbeing, and then define and measure the relationship between these many wellbeing influencing factors. A third requirement for effective policy is to be able to measure the impact these factors have by measuring the change in wellbeing that results as factors change; this makes it possible to target those contributors that should most improve wellbeing. Finally, by better understanding and measuring the impacts on wellbeing, this enables us to assess the effectiveness of the policy.

In the remainder of this chapter, I explain how my research aims fit within these general objectives of wellbeing research in economics. I then identify non-trivial research gaps and propose an agenda of research to elicit a deeper understanding of the issues.

The self-proclaimed discipline of 'happiness economics' or 'economics of wellbeing' became a vibrant field of research following the seminal work by Easterlin (Easterlin Paradox) (Easterlin, 1974; Easterlin et al., 2010) and has experienced significant growth in recent years (Clark et al., 2008; Frey, 2018). The growth in interest in *subjective* wellbeing can be seen as a reflection of current societal trends in the Western world that place a high value in the individual and subjective views about one's life. It also follows the recognition

that wellbeing includes positive elements that go beyond economic affluence (Diener et al., 1999).

Some of the wellbeing literature has focused on the relationship between happiness and fixed personality traits that are thought to be determinants of happiness, however the vast majority of economists have been interested in explanatory variables that relate to individual current situation (family, income health status) and the social and economic environment where the individual lives (unemployment rate, income inequality, environmental amenities) (Ferrer-i-Carbonell, 2013). The policy implications of such a line of research are obvious, it is about answering the question: "what makes people happy?"

Subjective wellbeing has been defined in the psychology literature as follows:

> *"…refers to all types of evaluations, positive or negative, that people make of their lives. It includes reflective cognitive evaluations, such as life satisfaction and work satisfaction, interest and engagement and affective reactions to life events such as joy and sadness." (Diener, 2006, p. 152)*

Diener further comments that subjective wellbeing is not a concept but:

> *"… an umbrella term for the different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live" (p.152)*

Reflecting this statement about the multi-dimensional nature of subjective wellbeing, the terms 'happiness' 'wellbeing' 'life satisfaction' and 'quality of life' have often been used interchangeably in the literature even though the terms are conceptually distinct. In this thesis, I choose to focus on life satisfaction as the criteria for individual wellbeing. The concepts, and my reasons for focusing on life satisfaction are explained in detail in Section 2.2.2 of Chapter 2. To summarise briefly, life satisfaction can be defined as:

> *"…a reflective assessment on a person's life or some aspects of it. […] Such assessments are the result of a judgement by the individual, rather than the description of an emotional state."(OECD, 2013, p. 30)*

The specific focus of this thesis is about geographical diversity in wellbeing. Why are people apparently happier (or more satisfied with their lives) in some places rather than others? There must be reasons that drive those differences. Those reasons may have to do with natural capital (climate, environment); they may also have to do with society and social

capital: how some places are different because people get on better; but in other places, people may feel less happy because they fear crime, or they don't trust the authorities. It may also be that happier people tend to congregate in some places and not others. This general enquiry can be articulated in the form of broad research questions that will be addressed in this thesis:

- Do individual and contextual factors influence variations in individual life satisfaction differently depending on the geographical location?
- How does the interaction between individual and contextual factors explain geographic heterogeneity in individual life satisfaction?
- How does perception of the local context contribute to individual life satisfaction compared to actual characteristics?
- What is the role of residential mobility in shaping the geographic differences in individual life satisfaction?

In the next sections of this chapter, I state the overall aim of this thesis, I then identify non-trivial research gaps and propose an agenda of research to elicit a deeper understanding of the issues. The chapter concludes with an outline of this thesis.

1.2 Overall aim of thesis

The overall aim of this thesis is to investigate and improve understanding of the factors that contribute to the geographical variations and spatial clustering in life satisfaction average scores. These factors may be contextual factors related to the natural environment and climate, or to the social and economic environment. They may also be the result of compositional effects reflecting the differences in people living at different locations.

1.3 Determination of research gaps and research objectives

1.3.1 Research strategy

This overall research aim guided my research strategy while exploring the literature and recognizing possible research gaps. My initial focus was on the contextual factors that had been identified in the literature as contributing/influencing individual wellbeing. The first group of factors relate to what has been referred to as natural capital, the second group as social capital (Costanza et al., 2013)[1]. The next stage of my investigation focused on the interface between the natural and social context, and individuals: since subjective wellbeing

[1] This specific typology of life satisfaction domains is explained in more details in Chapter 2, Section 2.2.4.2.

is by definition an individual cognitive process (Diener, 2006), the perception of that context is likely to be an important determinant of any individual evaluation about life satisfaction. Finally, it is likely that geographical variations in wellbeing scores may not entirely result from the influence of contextual factors. It is also possible that people with certain psychological traits and attitudes may cluster at specific locations as a result of residential mobility. This led me to investigate the mobility literature, in particular the examination of relationship between mobility and individual wellbeing.

The previous thought process led me to prepare the Venn diagram presented in Figure 1-1 to help visualise how potential research gaps and hence research objectives could be derived from the overall research aim. The starting point of this study is the observation that there are geographical variations in life satisfaction scores, and I aim to investigate the possible reasons for these variations. Each subsequent circle in the diagram represents a domain of possible reasons where research gaps are identified leading to research objectives. Firstly, I consider contextual factors linked to natural capital: the climate and the natural environment; then in the next circle I consider factors linked to human geography with a particular focus on social capital. The next circle labelled 'individual perceptions' represents the interface between the context and the individual. Finally in the outer circle, I explore compositional effects: how different individual characteristics and personality traits may affect residential mobility and explain spatial variations in life satisfaction scores.

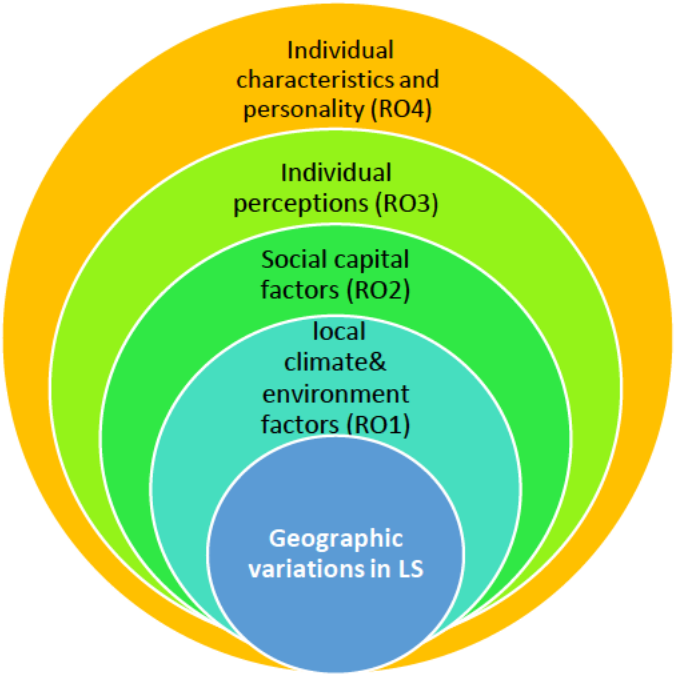

Figure 1-1: Articulation between main research theme and specific research objectives

1.3.2 Identification of research gaps

Identified research gaps are grouped into four categories corresponding to each circle in the Venn diagram. Within each category, several specific research gaps may be recognised.

1.3.2.1 Research gaps #1: local climate and environmental factors

The influence of climate variables on wellbeing has often been examined across different countries with a wide variety of climates, but since climate is likely to be perceived and experienced at a local level rather than a national level, it is essential to disaggregate climate data at the lowest possible level, i.e., at the regional or even local level (Brereton et al., 2008). Other research have looked at the influence of *local weather conditions* on experienced happiness in specific settings: for instance findings from the UK confirmed that higher temperatures, lower windspeed, sunshine and absence of rain were correlated with higher level of happiness of people are engaged in outdoor activities (MacKerron & Mourato, 2013). However, a first research gap is identified in our partial lack of understanding about the combined influence of regional variations in *long term* climate factors on evaluative wellbeing. This analysis can be challenging as multiple climate variables and other geographical amenities (for instance the proximity of water) may have a confounding effect on that influence (Barrington-Leigh, 2008). An attempt to investigate the impact of local climate conditions was made by Brereton et al. (2008) in Ireland. Many climate variables (sunshine, windiness, and precipitation) were found to be significantly associated with variations in wellbeing, however it is not clear whether this revealed a direct influence on wellbeing or whether their impact was due to correlation with other hidden factors.

A notable aspect of the Brereton et al study is that the context of the research, Ireland, is a small country with a very homogeneous climate (Brereton et al, 2008); this remark leads to the identification of a possible second research gap. It is highly likely that different climate norms would be established in regions with different climates and therefore climate variations will impact wellbeing differently (Hulme et al., 2009). *Inter-country* comparisons show evidence that high temperatures affect people differently in countries with a hot climate compared to countries with a temperate or cold climate (Maddison & Rehdanz, 2011). However, comparison between climate zones *within* the same country would allow us to

confirm whether the same climate attributes impact wellbeing differently without the noise created by diverging cultural or other socio-economic factors.[2]

Answering this question requires us to explore which climate attributes (and to what extent) affect people's wellbeing across locations where the climate is different. In statistical terms, this means that regression coefficients representing climate variables in a wellbeing explanatory model may vary depending on geographic location. This phenomenon is referred to as spatial non-stationarity.

1.3.2.2 Research gaps #2: social capital factors

Contextual socio-economic factors such as unemployment rate, average income, and income inequality have been investigated for their possible association with subjective wellbeing variations (Clark & Oswald, 1994; Florida & Mellander, 2016; Powdthavee, 2007). But 'social capital' factors that refer to the working of the community itself (Helliwell & Putnam, 2004) may also have an effect both at a macro level and an individual level; For example, personal community engagement may impact individual life satisfaction, however the overall level of community engagement in the neighbourhood where the individual lives may also have an influence on the wellbeing of all residents in the neighbourhood. The overall influence of social capital factors on wellbeing has been examined in a variety of studies (Aminzadeh et al., 2013; Aslam & Corrado, 2012; Neira et al., 2018), while other research have focused on specific factors such as community engagement (Yuan, 2016), perception of crime in the community (Ambrey et al., 2014) or institutional trust (Frey & Stutzer, 2000). An identified research gap here is that the literature is missing a systematic analysis of the impact of the multiple dimensions of social capital (Helliwell & Putnam, 2004) at neighbourhood scale in an urban context. Such an analysis may reveal the different levels (individual and macro) of interaction between contributors. A better understanding of these interactions may also give us an insight about the role of individual differences (compositional effects) versus contextual factors (contextual effects) in shaping spatial differences in wellbeing.

[2] Evidence suggests that climate and weather perceptions are shaped differently in linguistically and culturally different regions (Stewart, 2007).

1.3.2.3 Research gaps #3: individual perceptions of local climate and environmental conditions

Moving outwards from the contextual to the micro-influence, it is important to examine how the context is perceived by the individual. Here I focus on the natural environment and the climate. Previous wellbeing studies that examined the impact of local climate/ weather factors on wellbeing have used actual observations, for instance MacKerron and Mourato (2013), and Ahmadiani and Ferreira (2021). However, perception of the local climate is a cognitive exercise that is influenced by individual experience of climatic conditions (Harter et al., 2012; Hitchings, 2011; Hulme et al., 2009) and sometimes pre-existing beliefs (Kahan, 2013). It is therefore likely that subjective perception of the climate may differ from objective climate indicators. Several questions remain unanswered: Do these perceptions match actual observations? Are subjective perceptions better predictors of variations in wellbeing than actual observations?

The influence of natural environment factors such as environmental amenities and pollution on wellbeing has been examined more extensively than climate factors; both objective measurements and subjective perceptions have been used. Evidence suggests that subjective perceptions about the natural environment may be a better determinant of life satisfaction than actual indicators, whether it is about proximity and quality of greenspace amenities (Ambrey & Fleming, 2013; Hur et al., 2010) or about air pollution (Liao et al., 2015; MacKerron & Mourato, 2009). It also appears that different types of environmental exposures affects different components of wellbeing differently (M. White et al., 2017). However, only a handful of studies so far have examined the combined impact of multiple environmental and climate factors on wellbeing (Brereton et al., 2008; Ferreira & Moro, 2013; MacKerron & Mourato, 2013).

Another key gap in the existing literature is that little is known about *specific domain* satisfaction with the climate and the natural environment: how do subjective perceptions of climate and environmental attributes contribute to the cognitive evaluation of these respective domains? And to what extent are satisfaction with the local climate and satisfaction with the local environment associated with overall subjective wellbeing?

1.3.2.4 Research gaps #4: spatial clustering of life satisfaction scores

The evidence of geographic clustering in life satisfaction scores has been documented in several studies (Helliwell et al., 2019; Kubiszewski, Jarvis, et al., 2019); but very few

studies have examined why this clustering happens. So far, when trying to understand geographic variations in average life satisfaction scores, many researchers have focused on contextual factors, but there may also be compositional effects that explain variation in life satisfaction between areas: i.e., the possibility that on average, people with similar life satisfaction profile may choose to live in specific areas. A pertinent question about this spatial clustering was posed by Kubiszewski, Jarvis, et al. (2019, p. 9) in the conclusion of their study on spatial variations in contributors to life satisfaction:

> *"Do people move to live near others with shared values or does moving into a community change an individual's values?"*

Research that analysed spatial variations in psychological traits has posited that three of the mechanisms explaining spatial clustering in psychological traits are selective residential mobility, social influence and ecological influence (Rentfrow & Jokela, 2016). *Selective residential mobility* refers to how individual characteristics influence the environment where people decide to live. It is a process by which people with different psychological characteristics, different motivations and different happiness levels will move to different areas (Rentfrow & Jokela, 2016); more specifically it assumes that people move to places that they perceive as reinforcing their psychological needs (Jokela, 2009, 2014). *Social influence* refers to the effects that living among people within a given local environment has on a person's thoughts, actions and behaviour (Bond et al., 2012; Cohen, 1996). It is based on the assumption that traditions, customs and life style typical of a geographical area affect social norms and therefore impacts individual attitudes and behaviours (Hofstede, 2001; Hofstede & McCrae, 2004). *Ecological influence* originally refers to how epidemiological history of a region affects psychological processes and wellbeing (Schaller & Murray, 2008). The concept has been extended to the influence of features of the natural and built environment such as climate, terrain, and green space (Van de Vliert, 2013).

The influence of the social and ecological environment on individual wellbeing has been examined to some extent, in particular the impact of rural compared to urban residence on life satisfaction and hedonic wellbeing. Findings from a recent study by Jokela et al. (2015) in metropolitan London suggests that the clustering by neighbourhood observed for personality traits extends to life satisfaction scores. However, while the association between personality traits and selective mobility has received some limited attention (Jokela, 2020; Jokela et al., 2008), a key knowledge gap remains about the relationship between life

satisfaction and selective mobility to a specific location, and how the type of residence (for instance urban/ rural or local climate) may influence individual life satisfaction over time. It is believed that further knowledge on this issue would help address the question raised by Kubiszewski, Jarvis, et al. (2019).

1.3.3 Research Objectives

1.3.3.1 Research objective #1

Research objective #1 addresses the gaps related to local climate and environmental factors identified in Section 1.3.2.1. It is to determine the contribution of local climate factors to individual life satisfaction while controlling for the effects of demographic and socio-economic variables and other environmental variables. I will conduct this investigation at the national level and at spatially disaggregated level to examine the variations in the model(s) across different regions of Australia. Further knowledge about climatic impacts on life satisfaction is important for several reasons. Firstly, in a world where climate is apparently changing, this knowledge will inform predictions about how the anticipated changes may affect wellbeing and so help with designing policies to build an appropriate adaptive capacity. Secondly, an understanding of how spatial differences in climate interact with other factors to influence wellbeing may help explain why people move between regions and between countries. Specific research questions relating to this objective are expanded in Chapter 3.

1.3.3.2 Research objective #2

Research objective #2 addresses the gaps in relation to social capital identified in Section 1.3.2.2. It is to analyse the interaction between individual factors, household factors and geographic contextual factors in explaining the spatial differences in average life satisfaction scores between neighbourhoods in urban and suburban areas. This investigation will have a particular focus on social capital variables. A better knowledge of the interaction between contributing factors of wellbeing at different levels will inform public policy that aims to enhance social cohesion and trust within local communities. Specific questions relating to this objective are expanded in Chapter 4.

1.3.3.3 Research objective #3

Research objective #3 addresses the research gaps related to individual perceptions of local climate and environmental conditions identified in Section 1.3.2.3. It is to explore how perception of local climate and environmental factors contribute to overall life satisfaction. This exploration involves (i) the examination of how perceptions contribute to a specific

cognitive evaluation of each domain (climate and natural environment); (ii) an assessment of how the specific domain satisfactions are associated with overall life satisfaction. A better understanding of that process will assist policy initiatives that support adaptation to diverse, and potentially changing, local climates and promote the enjoyment of natural environment amenities. Specific questions relating to this objective are expanded in Chapter 5.

1.3.3.4 Research objective #4

Research objective #4 addresses the research gaps identified in Section 1.3.1.4. It is to explore how spatial clustering in life satisfaction could develop in association with selective mobility, social and ecological influence while controlling for personality traits and individual socio-demographic characteristics. This research objective incorporates two specific sub-objectives: firstly, to examine the influence of life satisfaction levels on selective mobility, for instance, moving from an urban area to a rural area or moving to an area with a different climate; secondly, to examine the influence of living in diverse types of geographic residence (urban / rural) or in different climate zones on life satisfaction over time. The results from this investigation will help understand why people move to different geographic residence and provide longitudinal evidence about the possible influence of geographic residence on wellbeing over time. Specific questions relating to this objective are expanded in Chapter 6.

1.4 Thesis outline

This thesis is structured into seven chapters followed by a list of references. Specific appendices are attached to Chapters 4, 5 and 6.

Chapter 1 (this chapter) introduces the research topic and sets out the overall research aim. This overall research aim helps identify research gaps, which leads to the articulation of specific research objectives.

Chapter 2 presents the context for the four individual studies included in this thesis: an overview of the scholarly literature pertaining to wellbeing research in the field of economics where key concepts and contentious issues are discussed. This consists in a critical review of the empirical literature on life satisfaction that formed the basis of a presentation to the 2021 international Conference on Business, Economics, Management, and Sustainability (BEMAS). Chapter 2 also includes a brief synopsis of Australia's geography and climate as well as summary descriptive statistics about life satisfaction across different regions of Australia. The chapter then describes the data that will be analysed to address the research

objectives stated earlier. The final section discusses methodological issues common to all studies in the thesis.

Chapters 3 to 6 address each the four research objectives stated in Section 1.3. Each chapter discusses the relevant literature, specific methodological issues and report the results from the analysis of the data. Findings are discussed in respect of the research objectives.

Chapter 3 uses pooled data from ten consecutive Household Income and Labour Dynamics in Australia (HILDA) surveys to estimate regression models representing the overall relationship between climate attributes such as temperature, rainfall and sunshine and individual life satisfaction while controlling for socio-economic factors. In the second part of the study, I examine whether the pattern of relationship between contributing factors and life satisfaction is spatially dependent.

In Chapter 4, Multi-level Modelling is used to explore the interactions between individual level and contextual level factors that contribute to LS with a particular focus on social capital. The study uses HILDA survey data from two large metropolitan areas of Australia to investigate how various contributors may explain spatial heterogeneity in wellbeing.

Chapter 5 presents a preliminary study where customised survey data is used to explore how domain specific cognitive evaluations of the local climate and the local environment contribute to overall life satisfaction. The contribution of subjective perceptions to their perspective domain evaluation is also examined as well as the relationship between subjective perception about climate attributes and corresponding actual observations. The paper from this study will be submitted for publication as a co-authored article within the next few months.

In Chapter 6, panel data collected by the HILDA surveys from 2013 to 2021 is used to explore the role of selective mobility and social and ecological influence in explaining spatial heterogeneity and clustering of average life satisfaction scores. The study first analyses the role of life satisfaction in selective mobility to specific types of areas and specific climate zones; then in a second stage, I test for the influence of residing in a particular area or a particular climate zone on life satisfaction over several years.

In Chapter 7, I summarize the key findings from the studies in Chapters 3 to 6 before highlighting the contribution to knowledge and the methodological contributions made by the research in this thesis, as well as the implications for policymakers in Australia and overseas.

I then discuss the limitations of the research and conclude with suggestions for future research.

Chapter 2 Context and methodology

In this chapter, I present the broad scholarly and geographic context for the studies included in this thesis and briefly explain the overall methodology. The chapter begins with a discussion of the shortcomings of Gross Domestic Product (GDP), and a brief presentation of alternative methods to measure human progress (Section 2.1). In Section 2.2, I introduce wellbeing research in economics, and discuss conceptual and measurement issues. In Section 2.3, I review the existing literature to identify previous findings and ascertain the depth of the relevant empirical evidence. The geographic context of this research is briefly described in Section 2.4, while recent data about life satisfaction in Australia is reported in Section 2.5. The rest of the chapter focusses on methodology with a presentation of the general design of the research (Section 2.6), and a description of the data sources (Section 2.7). The chapter concludes with a discussion of broad methodological issues common to all studies (Section 2.8).

This chapter is partly based on a conference paper that was presented at the International Conference on Business Economics Management and Sustainability in July 2021, and published as an edited book chapter; the citation for the published chapter is:

Lignier, P., Jarvis, D., Grainger, D., Chaiechi, T., 2022, *Geography, Climate and Life Satisfaction* in *Community Empowerment, Sustainable Cities and Transformative Economies*, Chaiechi, T. & Wood, J. (eds). Springer, Singapore.[3]

The published chapter has been edited for inclusion in this thesis to remove information already discussed elsewhere. Footnotes indicate where notable amendments have been made to the original article. Minor amendments have also been made to ensure consistent use of terminology within this thesis.

[3] Individual authors' contributions: P Lignier, conceptualisation, design and manuscript writing; D Jarvis, conceptual guidance, project supervision and critical manuscript review; D Grainger: project supervision and critical manuscript review; T Chaiechi, project supervision and critical manuscript review.

2.1 Beyond GDP[4]

2.1.1 What is wrong with GDP?

This section provides a brief overview of the conceptual shortcomings of Gross Domestic Product (GDP); alternative measures of welfare and wellbeing are described in Section 2.1.2

Almost ninety years after the concept was developed in the 1930s, GDP is still the dominant metric by which human societies measure their progress, and GDP per Capita often serves as a proxy measure for human wellbeing (van den Bergh, 2009). GDP is accepted as the standard measure of economic success by economists but also politicians, financiers, humanitarians even the public, and it has a huge influence on policy making (Daly & Cobb, 1989, p. 63; Eckersley, 2000; van den Bergh, 2009). There are however growing criticisms of GDP as a welfare indicator: many have pointed out the conceptual shortcomings of GDP in measuring *economic* welfare (Daly & Cobb, 1989; Stiglitz et al., 2009); others also argue that human wellbeing is about more than just economic welfare (Costanza et al., 2009; Kubiszewski et al., 2013; Nordhaus & Tobin, 1973; Stiglitz et al., 2009). Beyond challenging GDP as a measure of human progress, some have gone further in questioning the very idea of economic growth. Herman Daly advocates a steady-state economy on the ground that growth could become uneconomic (Daly, 2014); meanwhile the social-grassroots de-growth movement have been promoting the idea of "a society built on quality rather than on quantity, on cooperation rather than on competition […]" (Latouche 2003, quoted in Alier et al. (2010)). The analysis and discussion of these alternative paradigms are beyond the scope of this thesis which focuses on subjective wellbeing, a specific metric of human progress.

While there have been many recommendations to address the conceptual weaknesses of GDP (Daly & Cobb, 1989; Stiglitz et al., 2009), it remains that GDP is a narrow concept that does not adequately reflect human welfare (Costanza et al., 2009). For instance, GDP per capita does not adjust for the welfare effect of income distribution even though diminishing marginal utility predicts that rises in income will have more impact for families with low income (Costanza et al., 2013, p. 13). Moreover, GDP does not account for the fact that basic human needs like fresh water or shelter cannot be substituted with other types of consumptions (Posner & Costanza, 2011). Empirical evidence also supports the argument

[4] This section was titled 'Background and Introduction' in the published chapter. Some parts of the published have been expanded in the thesis version.

that GDP may not be a good indicator of individual wellbeing: while GDP per capita increased dramatically over the past five decades, alternative indices measuring wellbeing show either a flat trend or a decrease over the same period (the so-called Easterlin paradox) (Easterlin, 1995; Easterlin et al., 2010; Kubiszewski et al., 2013). Admittedly some of these findings have been subsequently qualified or disputed (Clark et al., 2008; Stevenson & Wolfers, 2008), including more recently (Killingsworth, 2021), nevertheless there is a growing recognition of the limitations of GDP among economists (van den Bergh, 2009). So, are there better ways of measuring human progress and wellbeing?

2.1.2 Alternative measures of progress

In response to these criticisms of GDP, alternative indicators measuring human progress have been put forward in the scholarly literature and by various global institutions. Examples of such indicators include adjusted economic indicators such as the Index of Sustainable Economic Welfare (Daly & Cobb, 1989) or composite indices like the United Nations Human Development Index that capture various relevant aspects of welfare and wellbeing (Bleys, 2012). A summary of the best-known economic indicators and composite indices is presented in Table 2-1.

2.1.2.1 Adjusted economic indicators

A well-known economic indicator derived from GDP is the Index of Sustainable Economic Welfare (ISEW) (Daly & Cobb, 1989) and its subsequent adaptation, the Genuine Progress Index (GPI) (Talberth et al., 2007). ISEW integrates principles of sustainability as it is based on the 'Hicksian' definition of income, i.e., income represents the maximum amount that can be consumed by a nation without eventual impoverishment (Daly & Cobb, 1989, p. 70). ISEW and GPI also address some of the conceptual problems of GDP: they separate positive from negative elements of market activities; they account for the value of non-marketed services from all types of capital; and they adjust for the depletion of capital (van den Bergh, 2009). GPI also accounts for the effect of income distribution (Posner & Costanza, 2011). Longitudinal studies using GPI or ISEW show that these indicators are generally correlated with GDP until a certain point in time when they diverge, confirming the "threshold hypothesis" developed by Max-Neef (1995)[5] (Posner & Costanza, 2011). ISEW

[5] Max -Neef's threshold hypothesis is stated as follows: "*For every society, there seems to be a period in which economic growth (as conventionally measured) brings about an improvement in the quality of life, but only up*

and GPI have been criticised by some authors as being methodically flawed and lacking theoretical foundation (Atkinson, 1995; Neumayer, 1999): it is argued that the concept of defensive expenses is not clearly defined; also, the index assumes that there is a link between income distribution and sustainability whereas empirical evidence suggests that this link is weak (Neumayer, 2000).

Table 2-1: Overview of adjusted economic indicators and composite indices

Name	Type	Authors	Description	Critique
Index of sustainable Economic Welfare (ISEW)	Adjusted economic indicator	Daly & Cobb (1989)	Adjusts GDP for non-market activities, capital depletion and environmental degradation.	Lack of theoretical foundations. Some methodological flaws (Atkinson 1995, Neumayer 1999, 2000).
Genuine Progress Index (GPI)	Adjusted economic indicator	Talberth, Cobb & Slattery (2007)	Same as ISEW. In addition. Accounts for income distribution, changes in environmental conditions and social capital.	Same as ISEW
Genuine Savings (GS)	Adjusted economic indicator	Hamilton & Clements (1999) World Bank	Focuses on maintaining or increasing wealth defined as the sum of economic, human, and natural capital.	Weak sustainability: neglects capital depreciation, only partially recognises informal activities (van den Bergh 2009).
Human Development Index (HDI)	Composite index	United Nations	Composite of Gross National Income pc, education index and life expectancy index.	Unit-less indices, components equally weighted (Diener & Suh 1997). Data reliability and comparability issues (Costanza et al. 2009).
Happy Planet Index (HPI)	Composite Index	New Economic Foundation	Composite of subjective wellbeing, life expectancy, income distribution and ecological footprint.	
Better Life Index (BLI)	Composite index	OECD	Composite of 11 indicators that represent conditions essential to the quality of life.	

to a point- the threshold point- beyond which, if there is more economic growth, quality of life may begin to deteriorate" (Max-Neef, 1995, p. 117).

2.1.2.2 Composite indices

The best-known composite indices include the United Nations Human Development Index (HDI) [6], the Happy Planet Index (HPI) developed by the New Economic Foundation [7] and the OECD Better Life Index (BLI)[8]. These indices are generally constructed from an assortment of economic, social, and environmental indicators. They are broader than ISEW and GPI, but are not generally expressed in dollar terms, so their interpretation requires comparison either in time or across nations. The main limitation of this type of measure is that variables that compose them may be chosen in an arbitrary fashion with disagreement among researchers about which variable to include (Diener & Suh, 1997; McAllistair, 2005). Weighting is another problem that can greatly affect the value of the composite index (Diener & Suh, 1997).

As shown in the 'critique' column of Table 2-1, neither adjusted economic indicators nor composite indices completely remedy the shortcomings of GDP. Furthermore, whereas the method for calculating GDP has been standardised, there are issues around the availability, reliability, comparability and timeliness of the data used in the calculation of many alternative indicators (Costanza et al., 2009). A fresh approach to finding an ideal indicator was put forward by various authors (Kahneman et al., 2004; van den Bergh, 2009); it has its roots in the findings from social psychology research on happiness and subjective wellbeing.

2.2 Wellbeing research in economics

2.2.1 Subjective wellbeing and utility

The current orthodoxy of economists uses the 'utility' concept. Utility can be construed as a subset of the broader notion of wellbeing (Larson et al., 2019). However unlike psychologists, economists have, for a long time, rejected the cardinal measurement and interpersonal comparisons of utility based on self-reported wellbeing on the grounds that it was an arbitrary and subjective measure (Gasper, 2004; Kristoffersen, 2010). Thus, for a long time, utility was deemed measurable only in the ordinal sense. The resulting difficulty and paradoxes of measuring ordinal utility led economists to rely on variables such as income and wealth as a proxy for utility (Kristoffersen, 2010).

[6] For more details see: http://hdr.undp.org/en/content/human-development-index-hdi

[7] For more details see: http://happyplanetindex.org/about

[8] For more details see: http://www.oecdbetterlifeindex.org/about/better-life-initiative/

The concept of subjective wellbeing has similarities with the economic concept of utility (Krueger & Schkade, 2008). The latter term was described by Jeremy Bentham as referring to pleasure and pain, happy and unhappy states (Fishburn, 1968). Under the utilitarian approach, people use preference ordering when making choices to allocate scarce resources (Kahneman et al., 1997). This process can then be represented by a utility function where people's choices and the ensuing utility is inferred from observable individual behaviour (Diener & Suh, 1997). Notable is that experienced utility (i.e. *ex-post* satisfaction related to the outcome of the decision), once believed to be non-measurable, is now considered by many to be measurable (Ferrer-i-Carbonell, 2013; H. Welsch & Ferreira, 2014). In short, there is now a broad acceptance (particularly in the economics of wellbeing literature) that self-reported wellbeing closely aligns with traditional welfare economic *ex-ante* decision utility and therefore is a valid and reliable proxy for individual utility measurement. (Ferrer-i-Carbonell, 2013; Kristoffersen, 2010).

2.2.2 'Subjective wellbeing', 'happiness' and 'life satisfaction'

Happiness and human wellbeing have long been topics of interest in the fields of philosophy and psychology. Philosophers, as far back as Aristotle, have attempted to *define* the concept of wellbeing (Gasper, 2004), while studies in psychology have mainly focused on the *measurement* of wellbeing based on self-reported subjective wellbeing (Kahneman et al., 1999). The widely shared position is that wellbeing extends beyond hedonism and instead involves self-actualisation and the realisation of one's true potential (Newton, 2007).

The terms life satisfaction[9], happiness and subjective wellbeing tend to be used interchangeably in the literature (Easterlin, 2003); however they are conceptually distinct (OECD, 2013). The psychology literature traditionally distinguishes between the hedonic component (affect) of wellbeing and the eudemonic[10] component (cognitive evaluation of achievements in one's life) (Deci & Ryan, 2008, p. 2). While happiness is generally associated with hedonic wellbeing (short-lived emotions), life satisfaction is more closely related to cognitive judgements and intrinsic goals (in the Aristotelian tradition) (Engelbrecht, 2009). To these traditional dimensions of 'happiness' and 'meaningfulness', a third distinctive dimension identified as 'a psychologically rich life' has recently been proposed

[9] The terminology 'quality of life' is sometimes used in the literature.

[10] Eudaimonia is a Greek term meaning "psychological flourishing"(OECD, 2013, p. 34).

(Oishi & Westgate, 2021). A psychologically rich life is defined by the authors as *"...a life characterized by a variety of interesting and perspective changing experiences"* (p 1).

The OECD guidelines on measuring wellbeing (2013) propose a measurement framework built on three dimensions: *evaluative, hedonic and eudaimonic* (Figure 2-1). The evaluative dimension is based on the individual cognitive assessment of one's own life (Kahneman & Krueger, 2006); the hedonic dimension reflects how respondents experience their lives (Graham & Nikolova, 2015); the eudaimonia dimension focuses on the functioning aspect of wellbeing, such as autonomy, resilience, social engagement and sense of purpose (Deci & Ryan, 2008). Whilst the validity and reliability of measurement for the evaluative and hedonic dimensions are largely recognised, the concept and assessment of eudaimonia is less well developed (OECD, 2013).

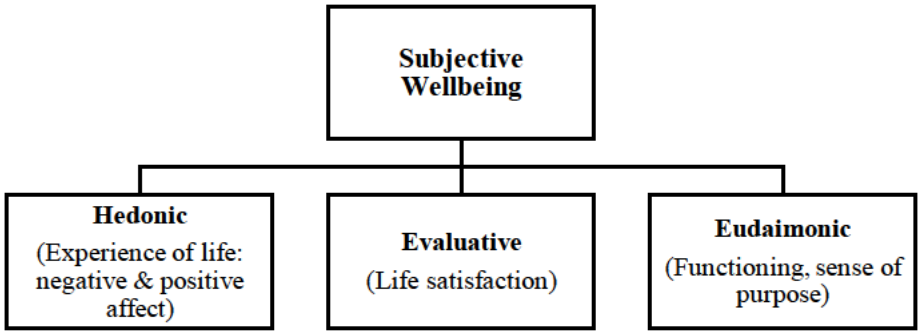

Figure 2-1: The three dimensions of wellbeing

(adapted from Graham & Nikolova 2015, Fig.1, p 164).

Life satisfaction is the concept used in the majority of wellbeing studies (Cummins, 2018) although the terms 'happiness' and 'subjective wellbeing' are also used, and comparisons across the different measures are common in the literature (Engelbrecht, 2009). Many authors have argued that life satisfaction correlates better with national predictors (Helliwell, 2003; Vemuri & Costanza, 2006). Despite some measurement contentions such as comparability and cardinality (discussed in Section 1.2.3), this concept is also favoured by economists because it is based on a cognitive assessment and therefore closely aligns with the conscious preference judgement implied from the definition of utility (Helliwell & Barrington-Leigh, 2010; Kristoffersen, 2017). Although some argue that life satisfaction and

hedonic wellbeing may be correlated to different factors[11], empirical evidence indicates a substantial overlap between the three dimensions with a high covariance, supporting the argument that a person will experience hedonic enjoyment if they fulfil their life in the eudaimonia sense (Deci & Ryan, 2008; Huta & Ryan, 2010). These arguments led me to decide that life satisfaction was the preferable dimension of subjective wellbeing to use in my thesis.

2.2.3 Measurement issues

Two issues have dominated the debate in the literature about the measurement of subjective wellbeing: the arbitrariness of wellbeing measurement, and the cardinality of those measures (Kristoffersen, 2010). Wellbeing is neither a direct, verifiable experience nor a known personal fact. It is based on a retrospective judgement that can be influenced by the respondent's mood and circumstances at the time of measurement (Kahneman & Krueger, 2006). We do not know where an individual with a particular score is positioned on the underlying psychological dimension, or what magnitude of change in the underlying dimension is represented by a one-unit difference on the observed score (Blanton & Jaccard, 2006).

The arbitrariness of life satisfaction scales mean that we cannot know for sure that two people who select the same score on the life satisfaction scale are equally satisfied (Kristoffersen, 2010). Validity doubts about measurements also arise because it is contended that some respondents may have no opinion about their own happiness and may instead report how happy they are expected to be (Veenhoven, 2008). The latter argument can be refuted on the ground of evidence showing that social desirability is actually a substantive characteristic that may enhance subjective wellbeing (Myers & Diener, 1995). There is also support for the validity of wellbeing measurements in their correlation with objective physiological and medical criteria (Kahneman & Krueger, 2006; Myers & Diener, 1995). Neuroscience research has also found a link between self-reported wellbeing measures and people's emotional states: for instance, people who smile frequently, who have positive emotions and display high sociability and extraversion tend to score higher on the life satisfaction scale (Kahneman & Krueger, 2006). The issue of interpersonal comparison is arguably laid to rest by the empirical evidence of a shared concept of satisfaction and

[11] Education and high income are well correlated to evaluative wellbeing, but health and care giving are strong predictors of hedonic wellbeing (Fastame et al., 2022; Kahneman & Deaton, 2010).

happiness: for instance, individuals are good at predicting other people's emotions and happiness by looking at pictures (Diener & Lucas, 1999). Also individuals belonging to the same language community translate verbal labels in a context free framework into similar score values (Van Praag, 1991).

Intertemporal comparison of wellbeing measurements has been questioned because the mental process involved in responding to questions on happiness or wellbeing may be fraught with error (Veenhoven, 2008). Individuals make an instant judgement based on pieces of information that happen to be available at the time (Veenhoven, 2008). It has also been contended that reported subjective wellbeing values can be affected by artefacts such as the type of scales used, the order of items, the timeframe of the questions, and other situational factors such as whether the measurement was collected through a face to face interview or through an anonymous survey (Diener et al., 1999; Myers & Diener, 1995). Self-tests and retests of wellbeing across individuals at an interval of one week show a correlation within a range of 0.5 to 0.8 between responses (Krueger & Schkade, 2008; Myers & Diener, 1995; Schimmack & Oishi, 2005). The correlation was higher when wellbeing was measured across several questions rather than a single question (OECD, 2013). This compares with correlation of 0.9 for re-interviews studies of self-reported earnings or level of education (Krueger & Schkade, 2008). These results suggest that there are certain limits on the reliability of the standard life satisfaction or wellbeing responses;[12] however they are not necessarily grounds for dismissing the method altogether as the idiosyncratic effects of recent circumstances on individual responses are averaged out when analysing responses from a representative sample (Kahneman & Krueger, 2006).

The second measurement issue, the cardinality of wellbeing measures, has consequences on how the data can be used in statistical analysis (Kristoffersen, 2010). Cardinality means that scores on the measurement scale represent equal variations on the underlying psychological dimension, i.e., intervals between the scores are presumed constant. This means that the distance between a 9 and a 10 on a 0-10 scale is assumed to be the same as the distance between other scores, such as 8 and 9, in terms of actual wellbeing (Kristoffersen, 2010). A number of researchers support the conservative view that happiness scores measured on a Likert scale are merely ordinal, i.e., although they can be ranked, they

[12] In general, a correlation of 0.7 is considered an acceptable level of consistency and reliability when comparing results from tests and re-tests (OECD, 2013, p. 48).

are not of interval quality (Katzner, 1998; Veenhoven, 1984). Despite the valid arguments presented by proponents of the ordinality position, most researchers in the field of wellbeing economics argue that the theoretical and empirical basis for assuming cardinality is strong (Kristoffersen, 2010; Ng, 1997) [13] This assumption of cardinality has received further support by the application of the response function for the MH5 Mental Health Index to life satisfaction measurements on the 0 to 10 scale (Kristoffersen, 2017).

2.2.4 The life satisfaction method

For the reasons stated in Section 2.2.2, life satisfaction is the chosen metric of wellbeing for this thesis, I will therefore refer to *life satisfaction* when discussing my analysis and my results. However, I will use alternative terminologies such as 'subjective wellbeing', 'happiness' and 'quality of life' when referring to literature that used those terms. In this section, I present the life satisfaction method in some detail. After describing the life satisfaction model used in economics research (Section 2.2.4.1), I discuss life satisfaction domains (Section 2.2.4.2), and the use of objective or subjective indicators (Section 2.2.4.3). Finally, I argue the usefulness of life satisfaction research for public policy and other fields of research (Section 2.2.4.4).

2.2.4.1 The life satisfaction model

Life satisfaction (LS) research in economics endeavours to investigate which factors influence overall individual LS. Typically, the methodology adopted in empirical research is to build a model similar to a utility function of the form $Y = f(x_1, x_2, \dots x_i, \dots x_n)$ where Y is self-reported overall individual LS and $(x_1, x_2, \dots x_i, \dots x_n)$ represents a string of explanatory variables relating to various domains of life (Stiglitz et al., 2009).

LS is generally measured by asking respondents a question of the type "*How satisfied are you with your life overall?"* (OECD, 2013) and requiring them to record their degree of satisfaction on a Likert scale graded from 'totally unsatisfied' to 'totally satisfied' or using a 0 to 10 or 1 to 10 point scale similar to the Cantril Ladder approach (Cantril, 1965). The underlying assumption is that interpersonal comparability of LS levels is allowed (Kristoffersen, 2010; Van Praag et al., 2003). The fundamental rationale behind LS research

[13] For a full discussion and further evidence on the "ordinality versus cardinality" views of wellbeing measures, please refer to Kristoffersen (2010) and Kristoffersen (2017).

is that if the appropriate indicators of LS are ascertained, then policy makers can identify the levers that can be used to improve LS in the population.

2.2.4.2 Life satisfaction domains

The nature of the explanatory variables included in the regression model will depend on the factors expected to contribute positively or negatively to overall LS. Factors that can potentially influence variations in overall individual LS can be grouped into two broad categories: genetic factors (Tellegen et al., 1988) and contextual factors (Emmons & Diener, 1986; Larsen & Ketelaar, 1991). Genetic factors include psychological and personality traits. Contextual factors are found in the physical, social, and economic *domains* that form the material of society. Different approaches can be used to conceptualise this environment (Van Kamp et al., 2003). Among other things, the differences between these conceptual frameworks relate to which domains and aspects of these domains are relevant to LS and to whether the emphasis should be given to objective attributes or subjective perceptions (Van Kamp et al., 2003).

LS domains are subjective collections of correlated factors and ideally weighted by relative importance (McAllistair, 2005). Cummins (1996) proposed a model based on seven life domains: material well-being, health, productivity, intimacy, safety, community, and emotional well-being. Cummins' approach was later refined by Van Praag et al. (2003) through the adoption a two-layer model to explain LS. In the first layer, a regression correlates LS and six life satisfaction domains (DS): job satisfaction, financial satisfaction, housing satisfaction, leisure satisfaction, health satisfaction and environment satisfaction. In the second layer, each DS is then regressed against a set of discrete explanatory variables; the same explanatory variables can be included in different DS regressions.

Various authors have argued that LS domains should be tested for their subjective relative importance rather than being considered of equal weighting. In a study conducted in the Mid-West US states, Hsieh (2012) used respondents ratings to rank the importance of the seven LS domains proposed by Cummins and found that religion was the most important domain followed by family life and friendships; financial situation was the lowest ranked domain (Hsieh, 2012). A similar approach was used by Larson (2009, 2010) in LS research conducted in tropical North Queensland. Larson's approach was guided by the idea that local communities should determine their own set of wellbeing factors. Twenty-seven well-being factors were thus identified and grouped into three domains: family and community; economy and services; natural environment (Larson, 2010, p. 2977). More recently, a case

study conducted in indigenous communities of North Queensland identifies 25 factors of wellbeing that conflated into three key wellbeing domains: country and culture, community and society, and individual and economy (Larson et al., 2020).

Costanza et al. (2013) propose an integrative approach to identify important LS domains, that considers opportunities (measured by objective indicators) and human needs (measured by subjective indicators). The authors identify opportunities by grouping them into four basic types of assets or 'capital'[14] *"...that are necessary to support wellbeing: built (physical) capital, human capital, social and cultural capital, and natural capital."*(Costanza et al., 2013, p. 9). Although the approach differs from Larson's, the LS domains identified by each author largely overlap as shown in Figure 2-2.

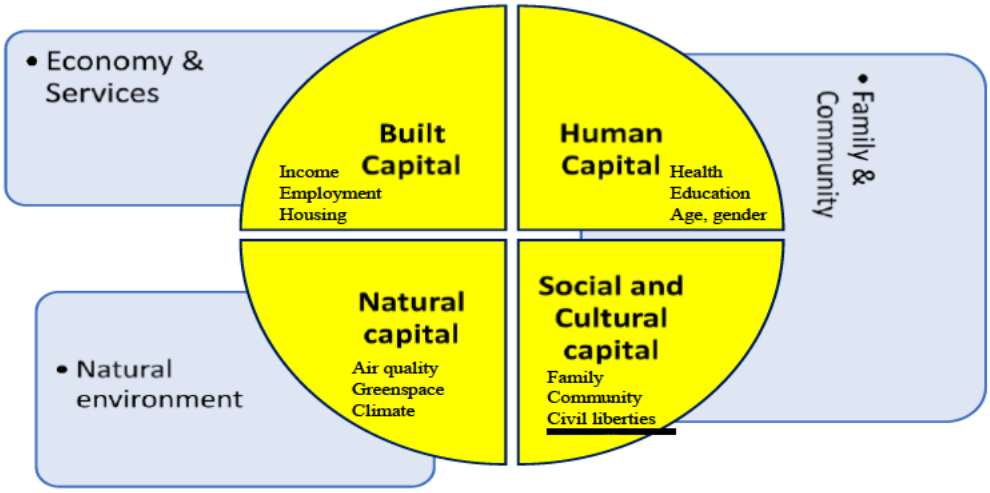

Figure 2-2: Opportunities 'capital' and life satisfaction domains: comparison between Costanza et al (2013) (pie) and Larson (2010) (rectangles) frameworks

2.2.4.3 Explanatory factors of life satisfaction: objective and subjective variables

Explanatory factors in the LS model can be either objective or subjective variables. Objective variables include demographic variables such as age, gender, or education level, but also social indicators that reflect people's circumstances in a particular cultural and

[14] The term "capital" or "assets" here have a much broader meaning than when associated with capitalism. They are used in the sense of "*a stock or accumulation or heritage, a patrimony received from the past and contributing to the welfare of the present and future. These assets overlap and interact in complex ways to produce all benefits that will contribute to quality of life"* (Costanza et al., 2013, p. 10).

geographical setting, based on quantitative statistics (e.g., unemployment level). Social indicators are assumed to measure 'objective' aspects of life that can help identify the appropriate policy lever to be used for corrective action (Diener & Suh, 1997). However, social indicators are not infallible: they can be contaminated by measurement errors or be biased. It is also contended that they do little to inform policy makers about public preferences (Veenhoven, 2002). Social indicators also have a selectivity problem: even though they are derived from objective measures, the process of selection of these measures might not be objective and the choice of particular social indicators may reflect the dominant normative values in a society (McAllistair, 2005).

Subjective variables included as explanatory variables in the LS model measure the responses to attitudinal questions reporting respondents' satisfaction or opinions regarding specific aspects of their lives. Examples of such questions include perception about the level of crime in the neighbourhood, or satisfaction with one's financial situation or one's health. Surprisingly, correlations between objective conditions and subjective appraisals tend to be weak, but subjective appraisals correlate more strongly than objective variables with overall LS (Kubiszewski et al., 2018). Individual perception of objective facts may deviate from reality: for instance, income satisfaction is hardly related to actual income (Veenhoven, 2002); similarly, perception of crime and actual level of crime in the neighbourhood differ widely (Ambrey et al., 2014). Even where there is a strong correlation between perception and reality, the relationship can be complex. For instance, Kubiszewski et al. (2018) found that satisfaction with one's financial situation was positively correlated with household income, but it was also correlated with demographic factors such as age and gender.

2.2.4.4 Usefulness of life satisfaction research

Meaningful and reliable measures of LS provide useful information about individual preferences. As already noted in Section 2.2.1, LS is a direct measure of *ex-post* utility that is gaining acceptance among economists, and this can potentially open numerous avenues for future research. However this possibility is dependent on the development of new theories to formalise the link between satisfaction, utility, preferences and behaviour (Ferrer-i-Carbonell, 2013).

LS research could also potentially provide a tool in the form of a "LS index" that would replace GDP as a measure of human progress. But is this desirable? Governments in Western European countries and even the Chinese government have stated that they wanted to pursue national happiness as a prime goal of policy (Frey & Gallus, 2013b). The

Sustainable Development Goals (SDG) index developed for the United Nations incorporate SDG 3 "Health and Wellbeing" (Sachs et al., 2019). However, many LS researchers caution against the development of such index for the fundamental reason that if national happiness became a policy goal, the information within the index could be distorted (Ferrer-i-Carbonell, 2013; Frey & Stutzer, 2012). There are two main reasons why this could happen Firstly, respondents to LS surveys might then engage in strategic responding with the expectation that the survey outcome is a judgement on government. Strategic responses undermine reliability of wellbeing evaluation and politicisation of happiness undermines its usefulness (Frey & Gallus, 2013a). Secondly, if a LS index became an indicator of government performance, politicians in power would have a strong incentive to manipulate it (Frey & Gallus, 2013b). Rather than aim at developing a LS index, authors in the LS research community suggest that research outcomes should instead inform public policy making about people's likes and dislikes and guide governments about the conditions they need to establish to make people happy (Ferrer-i-Carbonell, 2013; Frey & Stutzer, 2012).

2.3 Review of empirical evidence on life satisfaction[15]

In this section, I review the empirical evidence about the variations in LS levels across countries and regions (Section 2.3.1) before discussing the numerous factors that have been shown to contribute positively or negatively to LS (Section 2.3.2). Finally in Section 2.3.3, I examine the importance of geography as a context factor shaping individual LS.

2.3.1 Life satisfaction across nations and regions and over time

Cross-sectional comparisons show considerable variations in average LS between nations, as well as a strong correlation between economic development and high level of mean LS (Inglehardt et al., 2008). A comparison of mean LS scores between European regions in 2006 indicates higher average LS levels for people living in Northern Europe (including the UK), Spain and Switzerland and comparatively lower levels for France and Central and Eastern Europe (Aslam & Corrado, 2012).

At a smaller scale, inequality in individual LS among the population of a given nation can be observed. A few studies have grouped people into different categories based on their LS score (measured on a 0-10 scale): thriving (score 7-10); struggling (score: 5-6) and suffering (score: 0-4) (Andreasson & Birkjaer, 2018; Kubiszewski et al., 2020). Although a score of 7 and above is considered 'normal', as shown in Table 2-2 the proportion of people

[15] Some of the content in the published chapter has been expanded and restructured in the thesis version.

in each category varies widely even among European countries. Some of these differences could be attributed to different cultural perceptions (Andreasson & Birkjaer, 2018).

A large body of evidence tends to support earlier hypotheses by Easterlin (1974, 1995) that mean levels of well-being in advanced countries are stable over time. This was demonstrated by Inglehardt (1990) in a study of Western European countries from 1973 to 1988 and later confirmed by similar findings elsewhere (Diener & Oishi, 2000; Inglehardt & Klingemann, 2000; Kahneman & Krueger, 2006).

Table 2-2: Distribution of people's life satisfaction scores in selected countries*

Countries	**Suffering (0-4)**	**Struggling (5-6)**	**Thriving (7-10)**
Denmark	3.0%	5.1%	91.9%
Sweden	4.6%	10.3%	85.1%
Netherlands	4.3%	8.0%	87.7%
Germany	8.3%	14.2%	77.5%
United Kingdom	9.6%	15.5%	74.9%
France	17.0%	23.4%	59.6%
Russia	26.9%	34.7%	38.4%
Australia†	***1%***	***8%***	***91%***

* Adapted from Andreasson and Berkjaer 2018, Table 2, p 15.

† From Kubiszeswski et al 2020. p 5.

Evidence from the psychology and economics research literature suggest that factors that increase satisfaction with life, may not necessarily decrease dissatisfaction and vice-versa (Boes & Winkelmann, 2010). Findings from an Australian study (Ambrey & Fleming, 2014) indicate that between 2001 and 2010, negative deviation in LS (i.e., dissatisfaction with life) decreased by more than 18% on average; however results from the same study suggest that overall LS in Australia is declining over time. Based on panel data from household surveys covering the period 2001-2010, mean LS appears to increase between 2001 and 2003, then show an overall downward trend from 2003 onwards as well as a diminishing gap between males and females, largely due to declining LS scores among females (Ambrey & Fleming, 2014).

2.3.2 Factors contributing to life satisfaction

2.3.2.1 Overview

The nature of the explanatory variables included in the regression model will depend on the factors expected to contribute positively or negatively to overall LS. Many researchers who have studied the influence of contextual factors on LS have been disappointed by the relatively small effect sizes of those variables (Diener et al., 1999). The empirical evidence regarding factors found to significantly influence variations in individual LS is summarised in Table 2-3. In many instances, the relationship was found to be ambiguous or nonlinear. In the following discussion, I classify factors into two broad categories: personality and psychological factors, and socio-demographic and human capital factors. Two further categories linked to geographical context, environmental variables and social capital variables will be discussed in Section 2.3.3.

Table 2-3: Factors frequently found to influence variations in LS.

Factors with a positive influence	
Higher income	Higher income generally associated with higher levels of LS both at country level and micro-level. Strong evidence that relative income is more important to individual LS than absolute income (Ambrey & Fleming, 2014; Bonini, 2008; Shields, Price, & Wooden, 2009).
Being married or in a de-facto relationship	(Ambrey & Fleming, 2014; Blanchflower & Oswald, 2004; Brereton et al., 2008; Frey & Stutzer, 2000; Helliwell, 2003)
Being healthy	(Brereton et al., 2008; Diener et al., 1999; Helliwell, 2003; Kubiszewski et al., 2018)
Family relations and friendships*	Deemed important by 68% of respondents (Larson 2010). Neighbourly social interaction (Shields et al 2009) (Myers & Diener 1995)
Freedom, democracy, and governance*	Good governance, democracy and political freedom associated with higher levels of LS (Abdalah, Thompson, & Marks, 2008; Frey & Stutzer, 2000; Helliwell, 2003; Inglehardt, 1990; Inglehardt et al., 2008)
Factors with a negative influence	
Being unemployed	Blanchflower & Oswald, 2004; Bonini, 2008; Brereton, Clinch, & Ferreira, 2008; Clark & Oswald, 1994; Helliwell, 2003). Retired persons, full time students and part-time employees report higher LS than full-time employees (Ambrey & Fleming, 2014; Shields et al., 2009).
Crime levels*	Actual crime levels, perception of high crime level (Ambrey et al, 2014)
Ambiguous non-linear relationship	
Age	U shape relationship between age and LS with a minimum at late 30s or early 40s (Blanchflower & Oswald, 2004; Ferrer-i-Carbonell & Gowdy, 2007; Helliwell, 2003; Ambrey & Fleming 2014).
Gender	Ambiguous: some report that females have higher levels of LS (Blanchflower & Oswald, 2004; Brereton et al., 2008; Ferrer-i-Carbonell & Gowdy, 2007) others that gender is an insignificant factor (Stutzer & Frey, 2010).
Education	Depends on how education level is measured. Number of years of education found to have a positive influence (Blanchflower & Oswald 2004); but having a university degree found to be negatively associated with LS (Ambrey et al 2014).

* Social capital variables are discussed in Section 2.3.3.3

2.3.2.2 Personality and psychological factors

Empirical evidence suggests that demographic factors such as age, gender, and race account for less than 20% of the variance in wellbeing, while external variables account for less than 15% (Diener et al., 1999). This is confirmed by a recent Australian study where objective variables representing demographic and contextual characteristics could only explain about 12% of overall LS (Kubiszewski et al., 2018). The low predictive power of socio-demographic factors could be explained by the fact that personality has been found to be one of the strongest and most consistent predictors of LS (Layard, 2005). Evidence supporting the association between genetic factors and LS comes from a wide variety of research traditions and methodologies in the field of psychology (Diener et al., 1999). Following an experimental study of twins living apart and living together, Tellegen et al. (1988) concluded that about 40% of the variance in positive emotionality and 55% of the variance in negative emotionality can be explained by genetic factors. Later research by Lykken and Tellegen (1996) also found that 80% of the long-term stable component of subjective wellbeing: LS, is heritable. Later studies undertaken in Norway (Roysamb et al., 2018; Roysamb et al., 2003) broadly confirm these earlier findings.

Personality traits are one of the genetic traits that have been found to have a strong association with LS, in particular LS is strongly affected by stable personality traits such as extraversion and neuroticism (Costa & McCrae, 1980; Diener et al., 2018). Personality traits have also been found to have a very strong impact on the coefficients of some socio-economic variables (Clark et al., 2008; Ferrer-i-Carbonell & Frijters, 2004), however they are not typically observed in wellbeing economics studies and therefore usually form part of the error term.[16] As noted by Frijters and Beatton (2012), this omission might lead to the possibility of endogeneity within the LS model: unobserved personality traits that increase individual LS are also likely to be associated with higher income, higher level of education, having a partner and being healthier. Finally, the influence of personality on emotion/ wellbeing can also be mitigated by the impact of the external environment in which the individual is immersed (Emmons & Diener, 1986; Larsen & Ketelaar, 1991).

[16] Personality traits can be and have been included in some LS studies including the study presented in Chapter 6 of this thesis.

2.3.2.3 Socio-demographic and human capital factors

The contributor to wellbeing that has received the most attention from researchers is probably income. Research that focussed on the association between income and subjective wellbeing/LS were either country-level studies comparing GDP per capita and mean LS scores or micro-level studies that examined the relationship between individual / household income and individual LS scores.

While there seems to be a positive correlation between income and LS at the country level at *a certain point in time*, rising income *over time* is not associated with increased LS. Easterlin (1974) explains this paradox by the fact that material norms increase at the same rate as the actual income of society. Macro-level studies show that for poor countries average LS rises steeply as one moves from subsistence-level poverty to a modest level of economic security and then levels off. This effect peters out considerably and becomes almost zero for rich countries (Easterlin, 1995; Engelbrecht, 2009; Inglehardt et al., 2008; Myers & Diener, 1995).

In countries with an advanced economy, *relative* income at a micro-level seems more important to individual wellbeing than *absolute* income (Ambrey & Fleming, 2014; Bonini, 2008; Shields et al., 2009). The relative income hypothesis is confirmed in both space and time: social comparison, which means that relative income is at least twice as important to LS as actual income; income adaptation which means that the majority of individual effect of an increase in income on LS 'evaporates' within two years (Clark et al., 2008; Daly, 1987; Diener et al., 1999; Stutzer & Frey, 2010). Blanchflower and Oswald (2004) note that while the evidence indicates that richer people in the UK were generally more satisfied with their lives and that people got happier the closer their income came to that of rich people around them, the non-economic variables in happiness equations enter with large coefficients, relative to that of income.

Some findings suggest that income may affect different components of subjective wellbeing differently. A rise in income for low-income households is associated with a rise in both emotional wellbeing and evaluative wellbeing (LS). However past a threshold of US$75,000, the rise in emotional wellbeing stalls, while evaluative wellbeing keeps going up

until about US$95,000[17] (Jebb et al., 2018; Kahneman & Deaton, 2010). These conclusions have been recently challenged by Killingsworth (2021) who found no evidence of a plateau for experienced wellbeing or LS as household income rises.

There appears to be consensus in the literature that employment is associated with higher levels of LS, and that conversely unemployment has a negative effect on LS (Blanchflower & Oswald, 2004; Bonini, 2008; Brereton et al., 2008; Clark & Oswald, 1994; Helliwell, 2003). However evidence from Australia also reveals that people who have retired, people who do not participate in the work force, full-time students and part-time workers were more likely to report higher levels of LS than people who worked full-time (Ambrey & Fleming, 2014; Shields et al., 2009).

The contributions of demographic variables such as age, gender, health, religion, cultural identity, marital status, having children and education level have also been examined. Earlier inferences by Wilson (1967) that a happy person was necessarily a young person have generally been dismissed (Diener et al., 1999; Myers & Diener, 1995). While the psychology literature has reportedly found no evidence of a relationship pattern between age and happiness (Cantril, 1965; Palmore & Luikart, 1972), wellbeing research in economics has found some evidence that a relationship between age and LS exists in the form of a U shape curve with a minimum in the late 30s (Blanchflower & Oswald, 2004; Ferrer-i-Carbonell & Gowdy, 2007; Helliwell, 2003) or early 40s (Ambrey & Fleming, 2014; Shields et al., 2009). However, these results have been disputed in a comparative study based on data from the UK, Germany, and Australia where it is argued that the apparent U shape relationship could be due to fixed effects and data selectivity issues. In this instance, fixed effects may happen because of endogeneity issues as discussed earlier (Section 2.3.2.2). (Frijters & Beatton, 2012).

Religion and cultural identity have both been found to influence individual LS. People for whom religion is important in their lives are generally happier (Helliwell, 2003; Shields et al., 2009). Immigrants from non-English speaking countries living in Australia were found to be less happy even after controlling for English language skills (Ambrey & Fleming, 2014). This supports earlier findings in Europe that people living in their country of origin were

[17] According to the American Community Survey, at the time of the original study by Kahneman & Deaton in 2008, the median household income was US$52,000 and one third of households had an income above $US75,000.

generally happier than immigrants (Ferreira & Moro, 2013; Frey & Stutzer, 2000). In Australia, Indigenous people reported higher LS scores than non-indigenous people (Shields et al., 2009).

Both subjective level of satisfaction with one's health (Diener et al., 1999; Helliwell, 2003; Kubiszewski et al., 2018) and objective health conditions have been found to be highly correlated with LS. Respondents who have a poor health condition report lower levels of LS, with the negative impact of a severe long-term health condition particularly significant (Brereton et al., 2008; Shields et al., 2009). Conversely, factors such as 'having no long term health conditions' and 'daily exercise activity' were found to be significantly positive contributors to overall LS (Kubiszewski et al., 2018).

The relationship between education and LS is ambiguous. Some studies have found that higher education levels could enhance LS; however, the manner the "education" variable enters the regression equation seems to matter. For instance, the *number of years of education* was positively associated with LS while controlling for income in some studies (Blanchflower & Oswald, 2004; Brereton et al., 2008; Frey & Stutzer, 2000) but others have found that the *level of education* was not a significant contributor, and that in some cases a higher level of education (for instance having a university degree) was associated with lower LS (Ambrey & Fleming, 2014). One possible explanation proposed for this apparent paradox is that higher education may raise expectations that may not be met in reality (Clark & Oswald, 1994; Diener et al., 1999).

2.3.3 Life satisfaction in context: the relevance of geography, the contribution of the natural environment, climate, and contextual social capital

In this section I review the evidence about spatial heterogeneity in LS scores and discuss the influence that spatially dependent factors such as climate and environment, and social capital have on individual LS.

2.3.3.1 The relevance of geography: regional variations and scales of observation

Economic theory predicts that geography matters when it comes to the satisfaction of individual preferences: as people are generally free to move where they wish within the same country, people will move to areas where their individual preferences are better satisfied, leading to a general state of equilibrium (Tiebout, 1956). Although this hypothesis was partly confirmed by studies of regional variations in LS in the United States (Oswald & Wu, 2011), regional comparisons of LS points towards the existence of spatial heterogeneity in LS scores. In Australia, Ambrey and Fleming (2014) identified significant variations in the level

of LS between metropolitan areas (lower LS) and remote communities (higher LS), while Kubiszewski, Jarvis, et al. (2019) noted that average LS scores varied from 3 to almost 10 (on a scale of 0 to 10) across statistical areas even though they could not identify any discernible pattern. Clustering of LS scores has also been documented in the UK (Jokela et al., 2015), the US (Oswald & Wu, 2011) and Canada (Helliwell et al., 2019). Findings from China are more ambiguous: while one major study reported no significant variations in the average level of individual LS between regions (Zhou & Xie, 2016), in another research urban residents were found to be happier than residents of rural areas (Asadullah et al., 2018).

Some of these diverging results could be partly explained by the varying scales of aggregation of the data among studies. The data in the above China studies were aggregated at a large scale (large region and countrywide), while the statistical districts considered by LS research undertaken in Australia were a relatively small area with an average population of 10,000. Researchers that examined the impact of scale on LS models noted that some of the explanatory power of the LS regression model and information about which specific variables contribute to wellbeing was lost through aggregation (Ballas & Tranmer, 2012; Helliwell et al., 2019; Kubiszewski, Zakariyya, et al., 2019).

It is also possible that at different locations, factors influence overall LS differently. Two studies that used Geographically Weighted Regression analysis (Jarvis et al., 2017; Kubiszewski, Jarvis, et al., 2019) show that the variables with the largest coefficients in LS regression models are different across statistical areas. For instance, in the southeastern regions of Australia, increased age was found to have the greatest positive impact on LS, whereas in the West, household income was the variable with the highest positive coefficient (Kubiszewski, Jarvis, et al., 2019).

2.3.3.2 Contribution of the climate and natural environment to LS

Much has been written about the contribution of nature to human wellbeing. Existing research from various fields of inquiry provides evidence that nature fundamentally impacts human wellbeing both physically and mentally (Newton, 2007).[18] The Millennium Ecosystem Assessment (MEA) is a useful framework to analyse the links between nature and human wellbeing (Figure 2-3). According to this framework, ecosystem services contribute to human wellbeing by providing the basic necessities of life, security and health (Millenium

[18] For a comprehensive review of the evidence on the impact of the natural environment on wellbeing , see Newton (2007).

Ecosystem Assessment, 2003). They also support good social relations by enhancing mental and spiritual wellbeing; they contribute to social cohesion by promoting a sense of place (Newton, 2007).

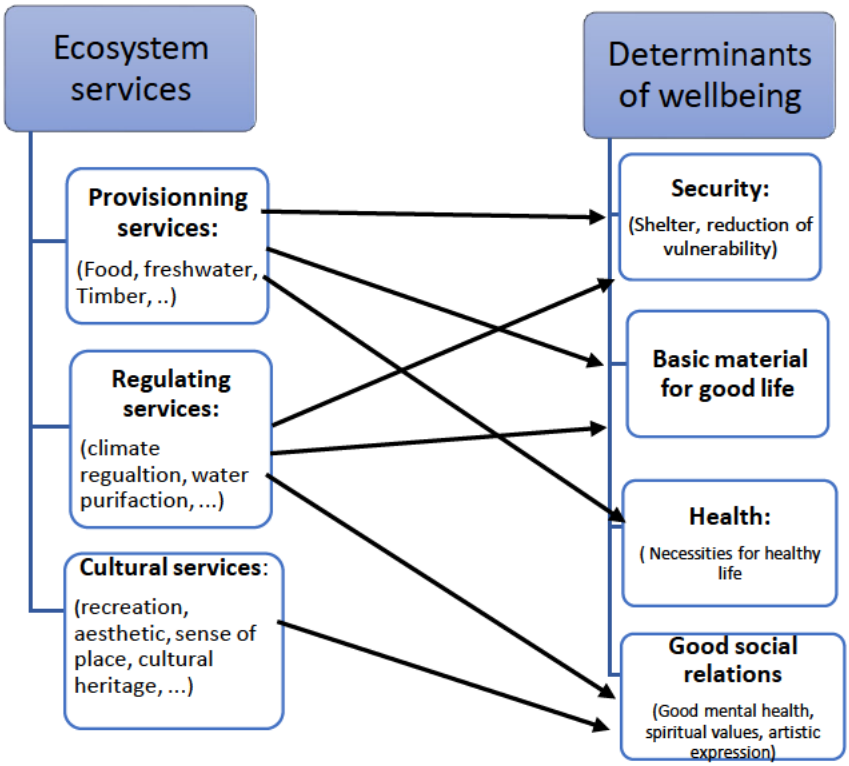

Figure 2-3: The MEA framework: ecosystem services and their links to human wellbeing.

Source: MEA (2003) (adapted)

The links identified within the MEA theoretical framework are illustrated by evidence from the empirical literature. Nature seems to have both quantity and quality effects on LS: quantity effects as in how much we can actually use and enjoy nature, for instance, proximity and accessibility to parks, beaches etc,… (Ambrey & Fleming, 2013; Takano et al., 2002); quality effects as in an environment that is not polluted or degraded (Speldewinde et al., 2011). Previous research has also shown that we do not necessarily have to live close to nature to benefit from it: the feeling of being connected to nature (regardless of whether we actually interact with and live in nature), has been linked to LS and wellbeing (Howell et al., 2011).

The empirical evidence regarding the influence of natural capital factors on LS is summarised in Table 2-4. Proxy variables such as Normalised Difference Vegetation Index

(NDVI)[19] adopted by Kubiszewski, Zakariyya, et al. (2019) and Kubiszewski, Jarvis, et al. (2019) in their Australian study have been found to be a significant positive predictor of individual LS when measured at a small spatial scale (local level). Empirical evidence provides support that proximity to greenspace (Ambrey & Fleming, 2013) and interaction with nature (Biedenweg et al., 2017) contributes positively to LS, and that the quality of the environment also matters (Ferreira & Moro, 2013) as well as the type of exposure (neighbourhood, regular or specific visit) (M. White et al., 2017). The positive correlation between LS and cultural ecosystem services from the Great Barrier Reef (Jarvis et al., 2017) confirms the hypothesis that nature can also contribute positively to LS regardless of use and proximity. Qualitative studies also provide evidence from in-depth interviews about linkages between nature exposure and different components of subjective wellbeing (Bell et al., 2015; Volker & Kistemann, 2013).

Table 2-4: Natural capital factors frequently found to influence variations in LS

Factor	
Proxy variables:	
Ecosystem Product Value per sq. km, Natural Capital per Capita	Macro proxy values found to be significantly contributing factors. (Abdalah et al., 2008; Engelbrecht, 2009; Vemuri & Costanza, 2006)
Normalised Difference Vegetation Index (NDVI)	NDVI highly significant at *lower* scales of aggregation (regional local level). (Kubiszewski, Zakariyya, et al., 2019)
Environmental dis-amenities: (negative influence) Air pollution, water pollution, noise pollution	Significant negative influence at both macro and micro levels: air pollution (Ferreira & Moro, 2013; Levinson, 2009; Luechinger, 2009; MacKerron & Mourato, 2009; H Welsch, 2002; H. Welsch, 2006); water pollution (Ferreira & Moro, 2013)proximity to land fill (Ferreira & Moro, 2013); airport noise (Van Praag & Baarsma, 2005) .
Environmental amenities: (positive influence) Greenspace, proximity/ visit to coast, cultural value of ecosystems	Urban, rural greenspace (Ambrey & Fleming, 2013; M. White et al., 2017); proximity/ visit to the coast (Bell et al., 2015; Ferreira & Moro, 2013); engagement with nature (Biedenweg et al., 2017) cultural value of Great Barrier Reef (Jarvis et al., 2017).

[19] "*NDVI is an index measuring the difference between visible light absorbed and infrared radiation reflected by vegetation. This measure changes due to vegetation density and greenness. The index value lies between -1 and +1. Higher values are associated with greater density and greenness, decreasing as vegetation comes under water stress, becomes diseased, or dies"* (Kubiszewski, Jarvis, et al., 2019).

Despite this significant gathering of evidence, two major issues have hampered empirical research on the influence of environmental factors on LS. Firstly, data is not always available at the right level of aggregation and often spatially incomplete: for instance, data on air quality is generally reported as a single value for whole countries or cities rather than at a local level (H. Welsch, 2006). Secondly, the framework of analysis developed by the MEA shows that links between environmental factors and human wellbeing are likely to be complex and intertwined. Moreover, as suggested in the Brereton et al. (2008) study, it is likely that natural environment variables interact with climate variables when influencing individual life satisfaction.

Climate and weather[20] affect physiological, psychological, social and economic conditions and as such are expected to have an impact on human wellbeing (Parker, 1995). The *weather* was found to have a transient effect on responses to LS survey (Barrington-Leigh, 2008; Frijters et al., 2020). Most of the evidence regarding the influence of *climate* comes from country-level studies (Maddison & Rehdanz, 2011; Rehdanz & Maddison, 2005; Van de Vliert et al., 2004). There is some indication that variations in temperatures and precipitation levels across countries were significant in explaining variations in LS; coinciding with earlier findings by Frijters and Van Praag (1998) that harsh climatic conditions in Russia (cold winters and high humidity in Summer) negatively affected both financial welfare and wellbeing. Single extreme climate events have also been found to impact LS at particular locations: for instance, drought in rural Australia (Caroll et al., 2009) and in the US (Berlemann & Eurich, 2021a); floods in the Philippines (C. J. Fernandez et al., 2019); hurricanes in the US (Ahmadiani & Ferreira, 2021; Berlemann & Eurich, 2021b; Calvo et al., 2015); and extreme temperature conditions in Mongolia (Kraehnert & Fluhrer, 2021) and China (Yang et al., 2021).

[20] *Climate is what you expect, weather is what you get…"* Mark Twain (National Center for Environmental Information, 2018). While weather refers to short term changes in the atmosphere and is experienced direct by our senses, climate is officially defined by the World Meteorological Organisation as a statistical construct based on 30 years of observations. However, climate can also be constructed as the product of people's experiences and memories of past events and of what is learned from previous generations. The perception of climate is also shaped by cultural interpretations In this sense, cultural and social expectations will influence expectations of future climate as much as statistical baselines (Hulme et al., 2009).

2.3.3.3 Social capital variables

The term social capital[21] is used by social scientists to refer to the social networks and associated effects such as trust and norms of reciprocity that influence human wellbeing (Coleman, 1988; Helliwell & Putnam, 2004). At an empirical level, it has been described as "*the shared knowledge, norms, rules and networks that facilitate collective experience within a neighbourhood*" (Vemuri et al., 2011, p. 6). Social capital (alongside natural capital, human capital and built capital) is also one of the domains contributing to human wellbeing identified by Costanza et al. (2013) and its importance has been documented in cross-country wellbeing studies (Helliwell & Putnam, 2004; Lawless & Lucas, 2010; Layard, 2005); as well as regional (Ballas & Thanis, 2022; Rentfrow et al., 2009) and neighbourhood studies (Aminzadeh et al., 2013; Vemuri et al., 2011). Human and social capital variables have also been incorporated in Australian LS empirical research (Kubiszewski, Jarvis, et al., 2019; Shields et al., 2009). Variables categorised under the umbrella of social capital can be classified into two sub-categories: micro-level variables relating to individual interactions within society and macro-level variables relating to social and political institutions.

Many of the factors identified by participants in a case study by Larson (2009) as contributing to their wellbeing were from the micro-level social domain. Family relations came in with the highest score (selected by 87% of participants) this was followed by community relation (57%). Findings from another Australian study suggest that 'neighbourly social interaction and support' is strongly and positively associated with individual LS for both males and females (Shields et al., 2009). Being able to spend time with family and friends and knowing that they are safe and well is also associated with higher LS according to a study by Myers and Diener (1995). Volunteering was documented to be a significant positive contributor to LS by Helliwell (2003) but results in Kubiszewski et al. (2018) were inconclusive in that respect. Both perception of crime and actual crime have a negative effect on LS. But while being victim of a crime has a strong negative impact on LS, overall perceived rates of crime have an adverse impact beyond those affected by crime (Ambrey et al., 2014).

[21] Some authors use the term 'human capital' when meaning 'social capital'. However following the framework in Costanza et al. (2013), we identify *human* capital as a set of personal level characteristics such as skills, knowledge, education and training, while *social* capital refers to group/ community level characteristics.

At a macro-level, there is solid evidence to suggest a positive link between good governance, political freedom and democracy, and LS levels (Abdalah et al., 2008; Frey & Stutzer, 2000; Helliwell, 2003; Inglehardt, 1990; Inglehardt et al., 2008). A few authors have argued that the relationship between democracy and free choice, and LS may be reciprocal: high levels of LS favours democracy, and democratic societies offer a context where a wider range of free choice is beneficial to wellbeing (Inglehardt et al., 2008; Veenhoven, 2000; H. Welsch, 2003).

Social trust that is the belief that those around you (neighbours, family etc.,) can be trusted is also considered to be a strong indicator of social capital at aggregate level (Helliwell & Putnam, 2004; Yuan, 2016).Empirical evidence indicates that a high national average level of interpersonal trust has a positive effect on subjective wellbeing. Similarly, research across several regions in Europe shows that a high level of social trust in the region was more significant as a positive contributor to LS that the personal level of trust (Aslam & Corrado, 2012). Social networking was also found to be strongly associated with both higher levels of LS and higher levels of happiness (Aslam & Corrado, 2012; Neira et al., 2018), but not with eudemonic wellbeing (Gilbert et al., 2016).

2.4 Geographical context for this thesis

Australia is the context chosen for the studies included in this thesis. Australia is believed to be an appropriate setting for an investigation of the geography of wellbeing for several reasons. The landmass of Australia is the size of a continent spanning several degrees of latitude and longitude and therefore embraces a wide diversity in terms of physical geography: climate and landscape (Twidale et al., 2023). Although the population of Australia is spread out over the whole continent, unlike other countries of settlement like Canada and the US, there are no obvious pattern of *spatial* diversity in terms of human geography and culture, except for some remote regions that are mostly inhabited by Aboriginal and Torres Strait Islanders communities (Peace, 2015). This means that the assumption of stable cultural norms and values holds when comparing different regions.[22]

[22] It is acknowledged that this assumption may not hold when comparing micro-regions: as mentioned above some rural and remote areas have a distinctly Aboriginal heritage and other areas have been marked by the culture of their distinctive immigration background, such as the predominant Italian heritage of the Ingham and the Northern Tableland regions in Queensland.

While the studies presented in Chapter 3 and Chapter 6 use the whole of Australia as a context, the study presented in Chapter 4 is focused on two metropolitan areas (Perth and Brisbane), while the data for the study in Chapter 5 was collected from specific regional areas in Queensland, Tasmania, and Western Australia. Australia has a culture and lifestyle comparable to other English-speaking nations such as the US, the UK, Canada, and New Zealand. Thus, evidence gathered from wellbeing studies undertaken in those countries and by extension other democratic countries with an advanced economy are likely to be relevant for the purpose of the research presented in this thesis. Similarly, findings from my research will have relevance and applicability for the same countries.

2.4.1 Brief overview of Australia's geography and climate

Australia is a large size country (7,686,000 km^2), with a relatively small population (26.5 million in 2023), as a corollary it is one of the least densely populated country in the world (density 3.3/ km^2). Much of the Australian population resides in a narrow coastal strip from Adelaide in South Australia to the northeastern tropical city of Cairns, with two additional areas of settlement in southwestern Western Australia and the Top End around Darwin (See Figure 2-4). The interior of the country as well as large stretches of the southern, western, and northern coastline are sparsely inhabited. Moreover, a significant proportion of the population (64%) is concentrated in five large metropolitan areas (Australian Bureau of Statistics, 2021-22) (Figure 2-5).

The Australian landmass spans several major climate zones ranging from temperate to equatorial according to the Köppen classification (Figure 2-6) (Bureau of Meteorology, 2005). Rainfall is characterised by high variability across space ranging from an annual average of less than 200 mm in the Simpson desert to more than 3,000 mm on the Cassowary Coast in Far North Queensland and on the west coast of Tasmania. It also fluctuates significantly from one year to the next subject to the influence of climate drivers such as the El Nino/ La Nina Oscillation, the Indian Ocean Dipole and the Southern Annular Mode (Bureau of Meteorology, 2010). Average temperatures range from cool in the Alpine country and central Tasmania to hot in the arid interior in central and northern Australia. Extreme cold temperatures are rare, however temperatures maximum over 45°C are commonly recorded at many locations. Australia experiences regular extreme weather events including bushfires (e.g., 2019 Black summer), multi-year droughts (e.g., millennial drought) and floods (e.g., 2022 floods in southeast Queensland and New South Wales (NSW) and 2023

floods in Far North Queensland). The tropical coast also experiences occasional destructive cyclones (Cyclone Yasi 2011, Cyclone Debbie 2017) (Bureau of Meteorology, 2023).

The overwhelming majority of the population of NSW, Victoria, South Australia, Western Australia, and Tasmania reside in a temperate zone with reliable rainfall and moderate temperatures although some urban locations are exposed to extreme events. About 80% of Queensland residents live in a sub-tropical climate while people in Northern Queensland, the Top End of the Northern Territory and the Kimberley region enjoy a truly tropical climate with distinct wet and dry seasons.

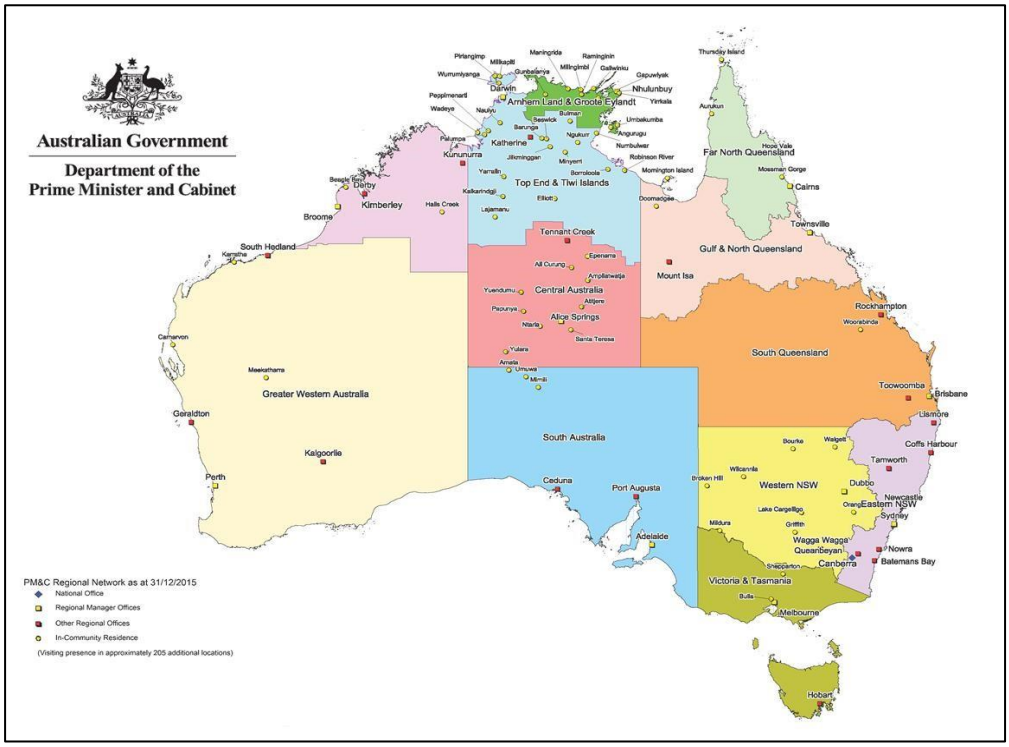

Figure 2-4 Australia: states, regions, and cities

Source: Australia Map360 https://australiamap360.com/australia-region-map

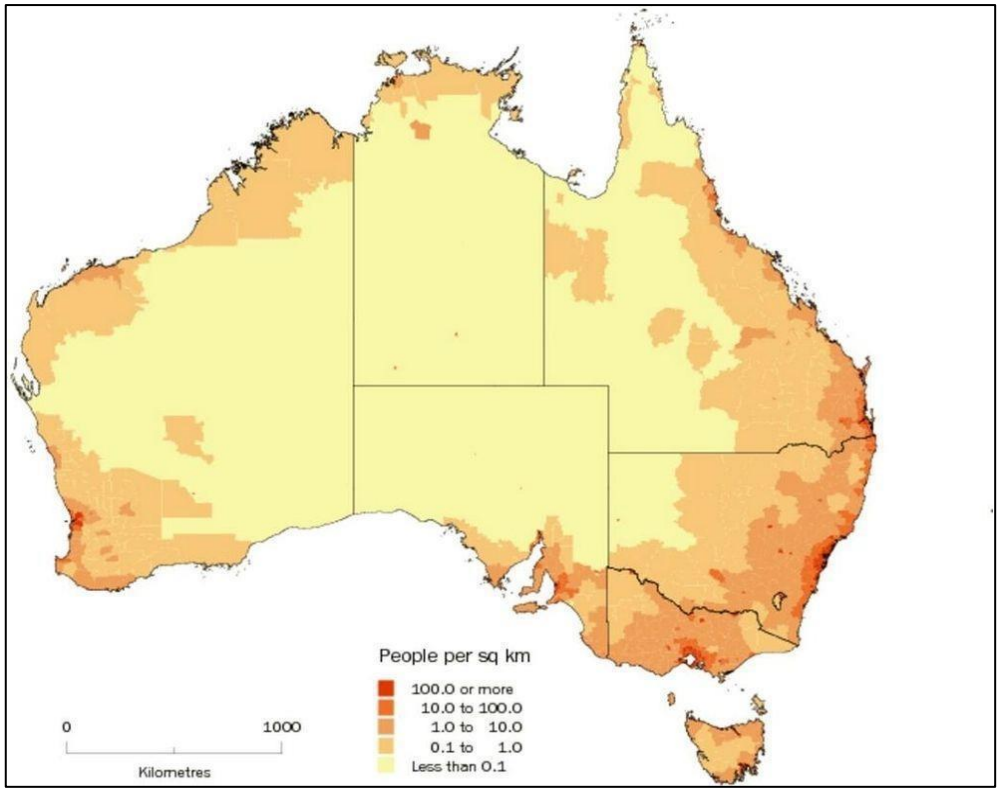

Figure 2-5: Australia: population density

(Source: AustraliaMap360: https://australiamap360.com/australia-population-map)

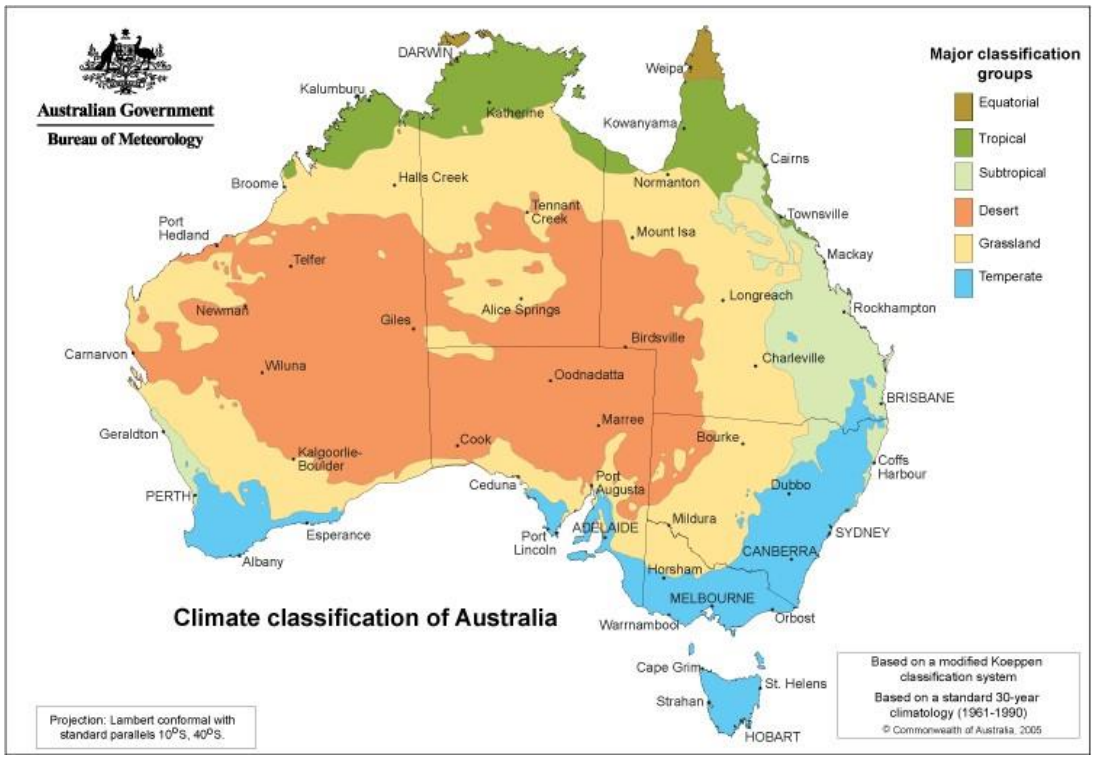

Figure 2-6 Australia: climate zones (Köppen classification)

Source: Bureau of Meteorology: http://www.bom.gov.au/climate/maps/averages/climate-classification/?maptype=kpngrp

2.5 Life satisfaction in Australia

2.5.1 International comparisons

Cross-country comparisons allow to evaluate the level of LS in Australia relatively to other countries. According to the latest data released by the OECD (2020), Australia has an average LS score of 7.1 (on a 0 to 10 scale) and ranks 13 out of 49 countries (Table 2-5). This compares to an average LS of 6.7 across the OECD. Australians seem to be more satisfied with their lives than residents of the UK or Japan, but not as happy as New Zealanders and residents of the Netherlands. This LS score of 7.1 compares with an average LS score of 7.9 calculated from 172,824 observations. in the pooled HILDA data collected from 2011-2020 The difference between the two values might be explained by the composition of the samples of respondents.[23]

Table 2-5 Average life satisfaction scores in selected OECD countries

Country	Average LS score (on 0-10 scale)	Rank
Finland	7.9	1
Netherlands	7.5	5
Germany	7.3	8
New Zealand	7.3	10
Australia	***7.1***	***13***
United States	7	14
Canada	7	16
United Kingdom	6.8	19
France	6.7	20
Japan	6.1	31
Russia	5.5	49

Source: OECD (2020)

2.5.2 Spatial diversity of LS within Australia

Before discussing spatial diversity of LS within Australia, it is important to examine several possible spatial units of observation, as the level of geographic resolution is very important when accounting for LS (Helliwell et al., 2019). The Australian Statistical Geography Standard (ASGS) is a framework developed by the Australian Bureau of Statistics (ABS) to organise the spatial units or regions for which it collects, releases and analyses

[23] The age group with the highest representation in the OECD sample for Australia was 15-24 (OECD, 2020); by comparison the average age for the HILDA sample was 42.6.

statistics (Australian Bureau of Statistics, 2016). There are currently four main hierarchical structures designated as Statistical Areas Levels 1, 2, 3 and 4 (SA1, SA2, SA2, SA4). According to the ABS, the structure is organised around the functional areas of cities, suburbs, towns, or localities, consequently the population and areas of units within the same level vary significantly as shown in Table 2-6.

Table 2-6 Statistical areas of ASGS main structure (2016)

Statistical Unit	**SA1**	**SA2**	**SA3**	**SA4**
Population range	200-800	3,000-25,000	30,000-130,000	100,000-500,000
Number (2016)	57,523	2,310	358	107

Source: ABS (2016): https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/1270.0.55.001Main+Features10018July%202016?OpenDocument

Based on the HILDA data, it is possible to map average LS scores by statistical units at different levels of observation. As noted by Kubiszewski, Zakariyya, et al. (2019), the degree of variation in mean LS score between areas depends on the spatial scale (Table 2-7). When the spatial scale of observation is large (State or Territory) the variations in mean LS between areas is small; by comparison, the variation in LS *between* small scale areas (SA1) is quite large. Small areas tend to be more homogeneous than large areas as shown by the value of the Standard Deviation of LS *within* the area. The main limitation to this approach is that very small unit of observations (SA1) tend to have very few observations in the HILDA sample. As noted by Helliwell et al. (2019) in relation to their Canada study, LS mean scores measured at a very small scale may have a large individual idiosyncratic component which might bias the interpretation of results. For this reason, the SA2 unit is believed to be the optimal size as it includes an acceptable number of observations (average 87 individuals per year in the HILDA sample) and provides a satisfactory level of granularity.

Table 2-7 Average LS and average LS variations *between* and *within* areas at different scales of observation*

	SA1	**SA2**	**SA3**	**SA4**	**State/ Terr**
Mean LS score†	7.928	7.893	7.936	7.955	7.964
Std Dev of LS between areas†	1.146	0.567	0.293	0.158	0.081
Std Dev of LS within area†	0.855	1.316	1.405	1.438	1.419

* Table is based on Kubiszewski, Zakariyya, et al. (2019) , Table 3, p 9

† Based on pooled HILDA data for period 2011 to 2020

The map in Figure 2-7 shows the distribution of LS mean scores for the period 2011-2020 from the HILDA data across Australia using the SA2 spatial scale. Although the map shows some evidence of regional clustering, there is no discernible pattern. The presence of spatial non-stationarity (i.e., the spatial variation in the patterns of relationship between regressors and LS) is confirmed by the highly significant Koenker Breusch Pagan test. On the other hand, the Global Moran Index that measures spatial autocorrelation is not always significant, confirming the absence of pattern.[24] Figure 2-8 shows the detail of the spatial variation of LS mean at SA2 scale for the four largest metropolitan areas[25]. Geographical clustering is clearly apparent in all four areas: for instance, bayside neighbourhoods in Melbourne have a higher average level of LS while outer northern suburbs show below average LS scores. Circled areas on the map in Figure 2-7 indicates the areas specifically selected for the studies in Chapters 4 and 5.

[24] See further discussion of this topic in Chapter 3.

[25] Statistical units are defined based on population; therefore, SA2 in urban areas have much smaller geographic areas compared to rural or remote SA2.

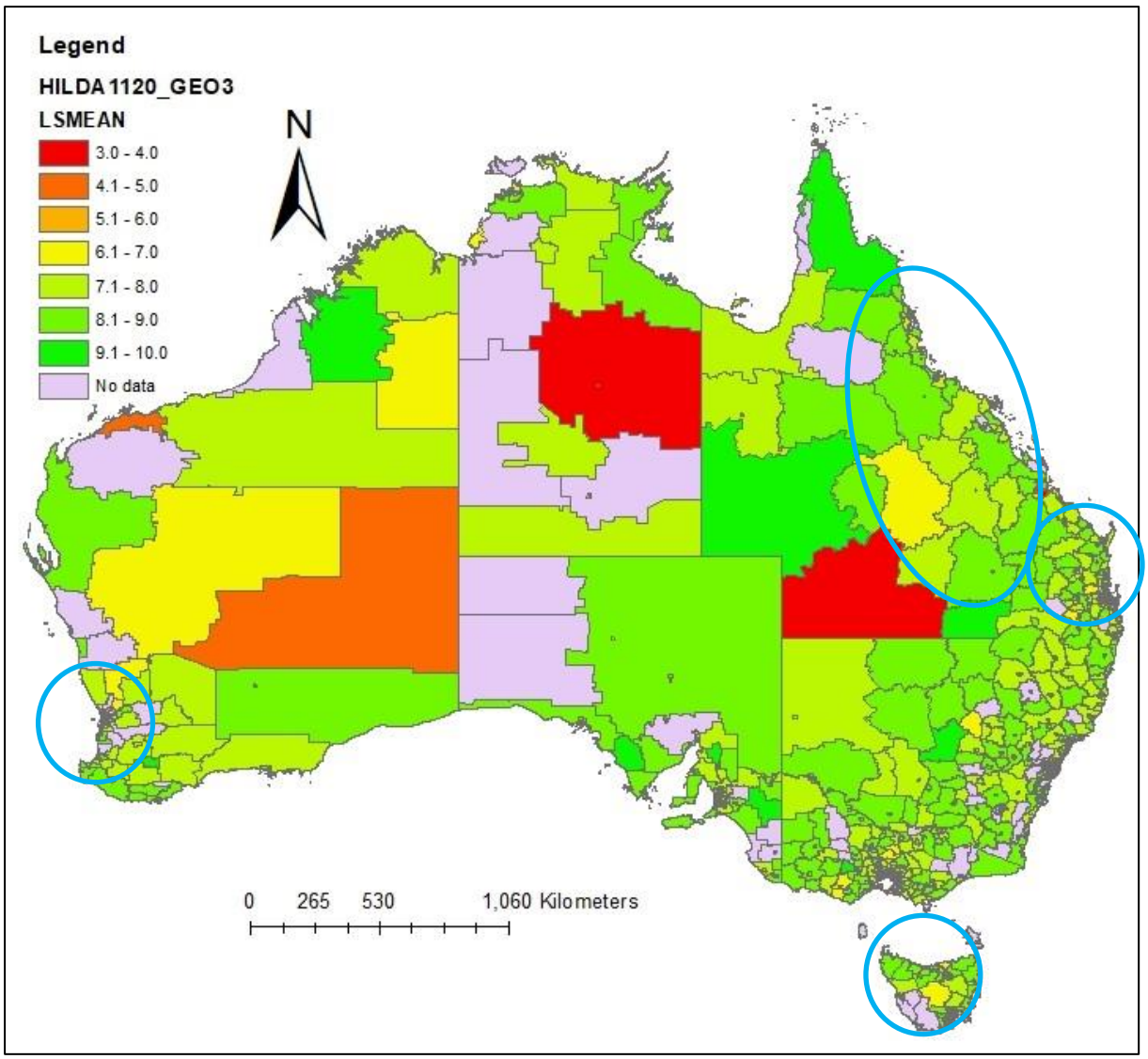

Figure 2-7: Australia: mean level of life satisfaction by SA2 for the period 2011-2020

Data source: HILDA. Areas covered by specific studies in this thesis are circled in blue.

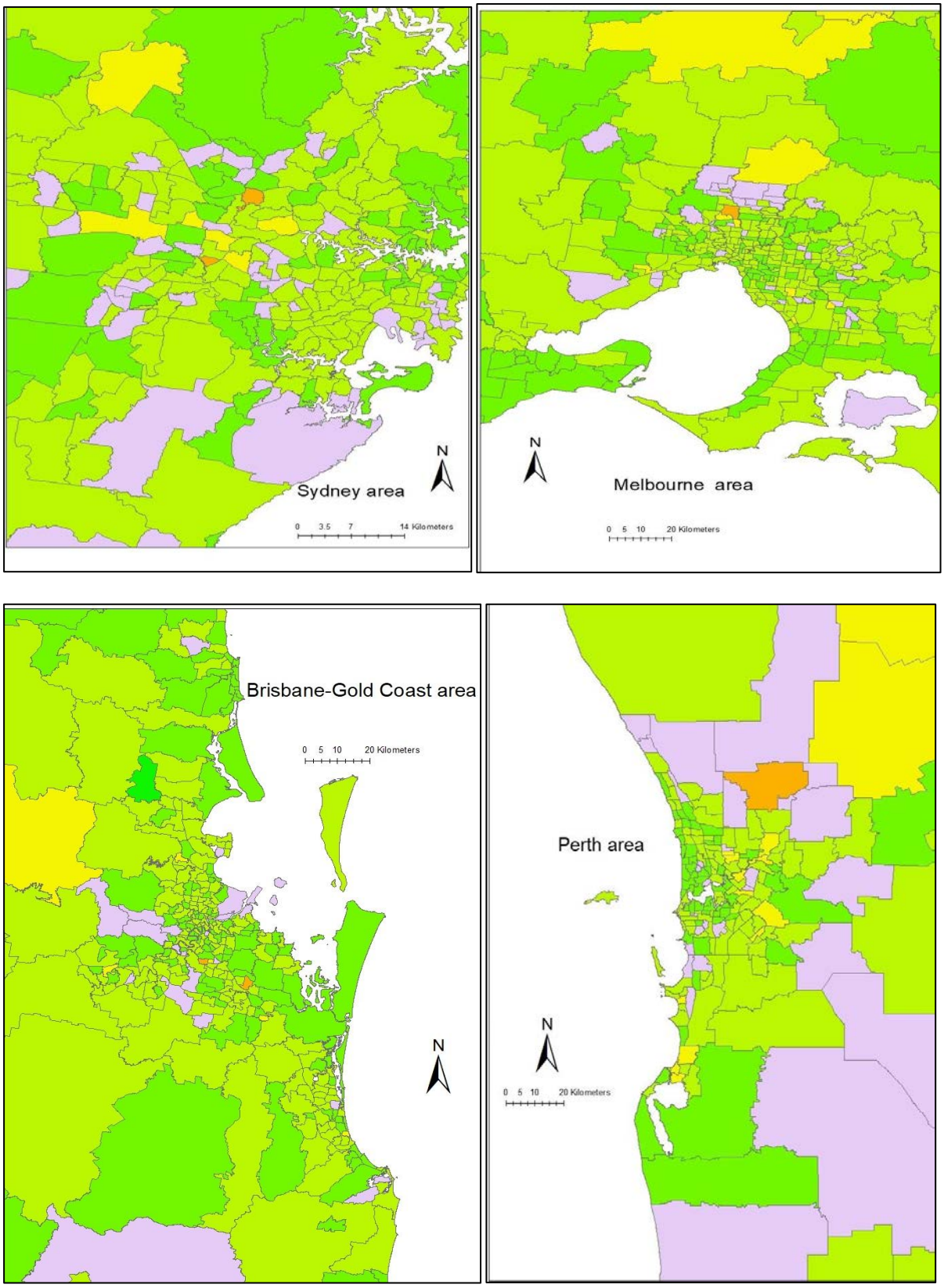

Figure 2-8: Australian metropolitan areas: mean level of life satisfaction by SA2 for the period 2011-2020

Data source: HILDA

2.6 General design of the project

The research adopts a quantitative design of enquiry where data collected through surveys is used to answer research questions derived from the literature (Creswell, 1994). This is consistent with the approach generally adopted in the welfare indicators empirical research (Posner & Costanza, 2011) and happiness /LS studies in particular (Diener et al., 1999). The dominant methodology used in LS studies involves the statistical analysis of a representative sample of data collected through large surveys of household and individual respondents. Examples of such data bases include the *World Value Survey* data used by Vemuri and Costanza (2006) and Engelbrecht (2009), the *British Household Panel* data used by Ferrer-i-Carbonell and Gowdy (2007) and (Ballas & Tranmer, 2012), *The European Social Survey* data used by Pittau et al (2010) and Aslam and Corrado (2012), the *Household Income and Labour Dynamics in Australia* data by Ambrey and Fleming (2014) and Kubiszewski et al (2018 & 2019), the *European Social Survey* data used by Pittau et al. (2010) and Aslam and Corrado (2012), the *Household Income and Labour Dynamics in Australia* data by Ambrey and Fleming (2014) and Kubiszewski et al (2018 & 2019). The leading statistical analysis approach is the development of regression models aiming to explain variations in self-reported LS by a set of independent variables that measure objective conditions or self-reported attitudes (Stiglitz et al., 2009, p. 148). In this thesis, I apply the LS regression approach described in Section 2.2.4.1.

Subject to the limitations imposed by the methodological issues described in Section 2.8, OLS regression analysis is applied in various forms throughout this thesis. In Chapter 3, I extend the OLS method by using Geographically Weighted Regression (GWR) that takes into consideration spatial variations in the pattern of relationship between regressors and LS. In Chapter 4, I apply a multi-level model regression model that allows for the hierarchical structure of the data and its interactions with LS. In Chapter 5, I use a framework of analysis based on multi-stage regressions. In Chapter 6, I use a panel data analysis where the regression method is adapted to the nature of the variables. The specific methodology used for each project is described in full details in the relevant chapters.

STATA Version 18 was used to estimate most regression models presented in the thesis while SPSS (Version 26) was also relied upon to estimate OLS models in Chapter 3. ArcGIS (Version 10.7.1), a geographic information system was used to conduct GWR in Chapter 3. This software also allowed the visual representation of regression results.

While the analysis pertaining to the research questions in this project is conducted within the context of Australia, it is anticipated that most findings are generalisable beyond Australia, in particular countries with an advanced economy and a similar political system. Nonetheless, it is acknowledged that some countries with an advanced economy and similar political system, may have different societal, cultural, and environmental attributes that may have bearing on the findings in this thesis.

2.7 Data selection

The projects included in this thesis rely on two primary sources of data: data collected from the Household Income and Labour Dynamics in Australia (HILDA) surveys; and data collected through a purpose designed survey that is used for the project in Chapter 5. In addition, the project utilises meteorological data collected by the Bureau of Meteorology of Australia (BOM).

2.7.1 HILDA data

To investigate the relationship between self-reported individual LS and potential contributing factors, the research analyses data collected through the HILDA[26] surveys. The HILDA surveys ultimately construct a national panel dataset for Australia. They have been conducted annually across all Australian states and territories since 2001 (Melbourne Institute, 2019). The latest data currently available is for 2020 (Wave 20); although I was able to use 2021 data from Wave 21 by the time the project reported in Chapter 6 was completed. The data is from a representative sample of around 17,000 respondents from more than 10,000 households interviewed every year; however not all individuals in the dataset have responded to every annual surveys (Melbourne Institute, 2022, p. 147). The original sample of people interviewed from Wave 1 had a size of 13,969 individuals to which a top up of 4,000 was added in Wave 11. Of the original sample, 58.7% were still participating in Wave 20 and 47.8 % had participated in all waves. (Melbourne Institute, 2022, p. 149). For the top-up sample, 70.9% of those interviewed in 2011 were still in Wave 20 and 65.6% had participated in all waves (p. 150). For the studies presented in this thesis, the HILDA data is either sourced from a single year (Chapter 4), pooled data from multiple years (Chapter 3) or built as a multi-year panel data (Chapter 6). The high level of re-interview means that it was possible to obtain a balanced dataset without discarding too many data.

[26] HILDA survey website: https://melbourneinstitute.unimelb.edu.au/hilda

The original HILDA sample was selected in 2001 using a stratified three-stage cluster design. The three stages broadly involved the selection of Census Collection District (CCD) within a state, then the selection of dwellings with each selected CCD, finally the selection of households within each dwelling (with a maximum of three households by dwelling) (Watson, 2012, p. 1). The selection design for the 2011 top-up sample was similar with minor adjustments. HILDA acknowledges that some groups are structurally missing from the sample, this includes people living in very-remote Australia and people who arrived or returned in Australia after 2001. The omission of the latter group was the main motivation for the recruitment of the top-up sample in 2011 (p. 5). Cross-sectional weights are calculated for each household and each respondent to reflect the probability of selection and correct for any sample bias when making inferences to the general population. Longitudinal weights are also available when using more than one year data (p. 32).

2.7.2 Development of a custom survey: sample selection and sampling technique

Additional data was collected through a separate custom-designed survey[27] to answer research questions for the project presented in Chapter 5. This additional data collection was necessary as the HILDA survey does not include any question relating to individual perceptions about local climatic and environmental conditions[28]. The collection and analysis of the data from this separate survey serves two purposes. Firstly, it allows to collect data about perceptions of local climatic conditions and test how well they match actual observations. Secondly it provides an opportunity to collect data about how people in different climate zones evaluate the local climate conditions and the local natural environment. This information is used to evaluate the association between satisfaction with the climate and individual LS, and satisfaction with the environment and individual LS. A copy of the survey instrument can be found in the Appendix at the end of this thesis.

The sampling frame for this survey was designed so that the final sample would include respondents from different climatic regions in Australia. The sample was primarily recruited from people living in regional areas of Australia as evidence suggest that people living outside large urban areas are more aware of climate patterns (Harter et al., 2012). In an

[27] The survey data collection process was conducted in accordance with JCU Human Research Ethics Committee approval H8397.

[28] As the distinction between weather and climate may not be obvious to all respondents, an explanatory note was included in the survey questionnaire to clarify the difference between the two concepts.

effort to control for any bias induced by the weather conditions at the time of completing the questionnaire (Barrington-Leigh, 2008; Brooks et al., 2017; Kahneman & Krueger, 2006), the survey was implemented in two consecutive waves: one during the winter period and one during the spring/summer period.

Three possible modes of data collection were considered for this survey: mail survey, internet survey or a mixture of both modes. Mail surveys allow an extensive coverage of residential households as 95% to 97% are accessible by mail and residential databases generally include postal addresses. Mail surveys are now considered very competitive with high cost in-person surveys in terms of response rates (Dillman et al., 2014, p. 12).

Internet surveys offer many advantages compared to sending a mail questionnaire. The first advantage is cost. Although the initial set-up costs might be high, there are potential savings on subsequent costs such as printing, postage, and data entry. Data quality is also improved by including consistency checks and prompts for missed questions (Sinclair et al., 2012). There are however three problems with pure internet surveys. Firstly, not all households have internet access, and the fact that the demographic characteristics of individuals who do not use the Internet differ sharply (older, less education, and lower incomes) may lead to a coverage bias (Dillman et al., 2014, p. 11). Secondly, comprehensive email databases are uncommon and even where databases are available, a significant proportion of these emails may bounce back because of the presence of spam filters. Thirdly, contact only by email often produces response rates that are lower than those achieved in mail surveys (Sinclair et al., 2012). Adding to the various reasons why people would choose not to respond to an email invitation to participate in a survey (Dillman et al., 2014, p. 20) is the fact that full screen laptops or desktop computers with keyboards are no longer the predominant way that many people connect to the Internet. Their small screens and input devices make reading and responding to survey requests quite difficult. Also young people continue to replace email communication with texts or social networking status updates, making it harder to reach this group (Dillman et al., 2014, p. 12).

There has been an increase in the adoption of mixed survey modes in recent years (Couper, 2011). Mixing modes is a way to ensure most members of the target population can be included in the sample frame and it can also improve response rates and reduce non-response error by appealing to different kinds of respondents (Dillman et al., 2014, p. 13). Using multiple survey modes as a means of communication to encourage response through a single mode may be a more powerful strategy to improve survey response and the quality of

those responses than simply providing an alternative mode for responding to a survey (Couper, 2011; Dillman et al., 2014, p. 13).

Based on these findings and in consideration of budget constraints, the optimum design for the proposed survey appeared to be a mixed mode design involving a single mode of data collection (internet-based survey) and multiple means of communication (mail and email). The result from a survey about water quality in Melbourne that used mixed modes of data collection and communication indicates that sending a personalised postcard inviting respondents to complete an internet survey (via a link or a QR code) increased response rates from 4.7% to 10.5% (Sinclair et al., 2012).

Finally, the covariates associated with respondents in both channels of communication are recorded to control for selection bias (Rubin, 2008). This is achieved by using a wave analysis following the method proposed by Lankford et al. (1995). Further detail about the sample selection and the questionnaire design and the implementation of the survey can be found in Chapter 5.

2.7.3 Climate data

According to biometeorologists, six categories of variables provide a complete climate/weather picture: temperature, precipitation, cloud cover/sunshine, humidity, wind and atmospheric pressure (San-Gil et al., 1991). Variables describing the climate can be either average measures or extreme values, e.g., the maximum temperature in Summer. Another form of measurement is based on counts, e.g., the number of days with a temperature under 5 °C. Extreme values are often more relevant than averages as they are more easily perceived (Cushing, 1987; Van de Vliert et al., 2004). Variables representing actual climate observations used in this thesis are shown in Table 2-8.

Climate data used in this thesis were obtained from the Australian Bureau of Meteorology (BOM) (Bureau of Meteorology, 2013). Weather observations generally cover the period 2000-2020. By averaging weather observations over a relatively long period of time, I assumed that the resulting data represents a climate trend that is fixed over time. A similar approach is adopted by the World Meteorological Organisation when calculating climate averages (Hulme et al., 2009) Climate data for each type of attribute was compiled

from daily observations by weather station for the whole period. The compilation was assisted by the availability of *ClimateQuery*[29], a specialised software tool.

[29] For further information about this software, see: (https://github.com/adamrehn/ClimateQuery).

Table 2-8: Actual climate observation variables used in this thesis

Variable	Category	Measure type
Annual rainfall	Precipitation	Average
No rainy days per year	Precipitation	Count
Rainfall in Driest Month	Precipitation	Extreme
Rainfall in Wettest month	Precipitation	Extreme
No months with rainfall < 30mm	Precipitation	Count
No Months with rainfall ≥ 100 mm	Precipitation	Count
Aver. Max Temperature	Temperature	Average
Aver. Min temperature	Temperature	Average
Maximum -Hottest Month	Temperature	Extreme
Minimum-Coolest Month	Temperature	Extreme
No days Max ≥30° C	Temperature	Count
No days Min ≤ 5° C	Temperature	Count
Average Mean temperature	Temperature	Average
Heating Degree Months (HDM):∑ Negative dev / mean temp 20°C	Temperature	Extreme
Cooling Degree Months (CDM) ∑ Positive dev / mean temp 20°C	Temperature	Extreme
Mean Temperature Coolest Month	Temperature	Average
Mean Temperature Hottest month	Temperature	Average
Annual sunshine hours	Sunshine/Cloud	Average
Solar exposure	Sunshine	Average
Average Humidity	Humidity	Average
No days Av. Hm. >75%	Humidity	Count
Max daily windspeed	Wind	Extreme

2.8 Methodological issues

2.8.1 Working with ordinal and categorical data

The issues surrounding the cardinality of wellbeing measures were discussed in Section 2.2.3. While the assumption of cardinality has not been accepted by all, many researchers in the field of wellbeing economics work within that assumption and use OLS regression models (Kristoffersen, 2010), however there are a few examples of LS studies that relied on the ordinality assumption and used alternative methods of analysis such as ordered probit (Ambrey & Fleming, 2014; Brereton et al., 2008; Ferrer-i-Carbonell & Gowdy, 2007). The assumption of cardinality of LS measures opens up more opportunities for quantitative analysis: namely, the possibility of using linear regression, and results that are easier to interpret (MacKerron & Mourato, 2009). Most researchers in the field have shown that working with the cardinality assumption produces similar results as working with the ordinality assumption when dealing with LS scores (Blanchflower & Oswald, 2011; Ferrer-i-Carbonell & Frijters, 2004). In this thesis, I rely on the cardinality assumption when regressing LS against explanatory factors. This assumption is extended to variables measured on a similar Cantril Ladder such as domain specific satisfaction. Logistic regression is used for the project reported in Chapter 6 where the dependent variable is either a binary variable or a pure ordinal variable describing climate zones or remoteness.

2.8.2 Gauss-Markov assumptions

The estimation of regression models relies on several assumptions so that coefficients in the model are BLUE (Best Linear Unbiased Estimators). These assumptions are derived from the Gauss-Markov theorem and for this reason are generally referred to as the Gauss-Markov assumptions (Johnson & Wichern, 2002). There are five main assumptions: 1) assumption of linearity, i.e., the relationship between the dependent variables and the regressor is assumed to be a linear relationship; 2) the data must be randomly sampled from the reference population; 3) non-collinearity between the regressors, i.e. the regressors aren't perfectly correlated with each other; 4) homoskedasticity, i.e., the error term is constant regardless of the values of the regressors; 5) all regressors are exogeneous variables; i.e. the regressors are not correlated to the error term (Lambert, 2013).

These five assumptions are systematically checked and discussed for all projects in this thesis. The breach of the last two assumptions: heteroskedasticity (breach of assumption of homoskedasticity) and endogeneity (breach of assumption of exogeneity) are common problems encountered by LS researchers and for this reason they need to be discussed separately.

2.8.3 Heteroskedasticity

One of the Gauss-Markov assumptions is that is that the error term does not increase or decrease with any of the explanatory variables, this assumption is called homoskedasticity, if the assumption is not true, the model has *heteroskedasticity*. There are several potential causes for heteroskedasticity; one is that the dependent variable is bounded which means that extreme values have restricted variances. This problem is relevant to LS typically measured on a bounded scale from 0 to 10. The second possible cause is model misspecification, meaning that some important variable(s) have been omitted or that variables included in the model are not in the correct form because their relationship with the dependent variable is not linear (Wooldridge, 2010, ch 8). The presence of heteroskedasticity in the model will not lead to biased estimates and the value of R^2 is unaffected. However, we no longer have BLUE estimators because standard errors are incorrect and so the level of significance is also incorrect (Lambert, 2013). Heteroskedasticity can be detected using visual graphs: for instance, where only one independent variable is suspected, estimated residuals can be plotted against that variable. However, this approach is not appropriate when dealing with a multivariate regression. Another visualisation method is the use of a P-P plot. Alternatively, heteroskedasticity can be detected by applying formal tests. Under these tests, the null

hypothesis H_0 is homoskedasticity; if H_0 is rejected, then we have heteroskedasticity. The most common test used to detect heteroskedasticity is the Breusch-Pagan test (Breusch & Pagan, 1979) with the White-Koenker test (Koenker, 1981; H. White, 1980) being an alternative test. Both tests are available in STATA and were systematically used to test for heteroskedasticity throughout this thesis. However, these tests have limitations in certain data configurations: they are asymptotically correct and so for small finite data sets this can present and issue. Where heteroskedasticity is suspected, robust standard errors are included in the regression model to control for this problem.

2.8.4 Endogeneity

Endogeneity has been identified as a potential problem in previous LS studies (Ambrey & Fleming, 2014; Ferreira & Moro, 2010; Frijters & Beatton, 2012). Endogeneity in a regression model arises when one of the regressors is correlated with the error term; the consequences of ignoring the endogeneity problem is that the coefficients of the regressors might be biased and inconsistent[30] (Wooldridge, 2010, p. 88). There are three potential causes for endogeneity in a regression model. The first is where a variable has been omitted from the regression. The second possible cause is where there are measurement errors in one or several independent variables. Finally, the source of endogeneity might be the presence of reverse causality between the dependent variable and one of the independent variables (Lambert, 2013).

Endogeneity in an OLS model can be tested using classic specification tests like the Hausman test or the Durbin-Wu-Hausman test (Davidson & McKinnon, 1993, p. 874). However, the use of these tests relies on the identification of instrumental variables, i.e., variables that potentially predict the suspected endogenous variable. Under the tests, the null hypothesis (H_0) is that the coefficient of the examined variable is efficient and so there is no difference between the coefficients in the original OLS regression and the regression using instrumental variables. If this is the case, then the variable is exogenous. However, if H_0 is rejected then the variable is considered endogenous (Cameron & Trivedi, 2010, p. 189).

When endogeneity is present, the problem can be addressed by adopting a multi-stage regression approach involving the use of instrumental variables (IV). The first stage consists

[30] 'Biased' coefficient mean that the value of the estimated coefficient $\hat{\beta}$ is not a good estimate of the value of the true coefficient β; 'inconsistent' coefficient means that the value of $\hat{\beta}$ does not converge towards β when the sample size n is large (Lambert, 2013).

in estimating the suspected endogenous variables against potential instrumental variables as well as the exogenous variables already in the original regression. The second stage consists in substituting the endogenous variable in the original regression with the predicted values of the same variable determined in the first stage (Lambert, 2013).

For example, let us assume the following regression model:

$$Y = \beta_0 + \beta_1 X + \beta_3 Z + \varepsilon \text{ (1)}$$

Where X is a suspected endogenous variable, Z is an exogenous variable and ε is the error term.

In the first stage, X is estimated as a dependent variable where regressors include the exogenous variables in Equation (1) + several instrumental variables:

$$X = \gamma_0 + \gamma_1 Z + \gamma_2 I + \gamma_2 J + \mu \text{ (2)}$$

Where I and J are instrumental variables predicting X , and μ is an error term.

In the second stage, we substitute X with the predicted value of X from Equation (2) in the structural equation:

$$Y = \delta_0 + \delta_1 Z + \delta_2 \hat{X} + \sigma \text{ (3)}$$

Where $\hat{X}$ is the predicted value of X from equation (2) and σ is an error term.

In this thesis, I evaluate for endogeneity in situations where endogeneity is suspected if potential instrumental variables can be identified and there is data available to measure them. Such a situation arises in the project presented in Chapter 5 where a suspected endogenous variable is identified, and multi-stage regression is applied to address the issue.

Chapter 3 Does the climate impact satisfaction with life? An Australian spatial study.

This chapter addresses Research Objective #1 identified in Chapter 1. The study was designed to reveal the contribution of climate factors to individual LS while controlling for socio-economic factors. To do so, I first estimate general OLS models with distinct categories of climate variables in several types of measurement. In the second part of the analysis, I use Geographically Weighted Regression to explore whether climate variables impact LS differently at different geographic locations. The analysis reveals that climate does have a small but significant impact on human wellbeing, and that the nature and significance of that impact vary spatially. This study is the first to investigate spatial non-stationarity in climate-LS predicting models within a large country covering multiple climate zones.

This chapter is based on a paper published in January 2023; the citation is as follows:

Lignier, P., Jarvis, D. Grainger, D. & Chaiechi, T. (2023). Does the climate impact satisfaction with life? An Australian spatial study. *Weather, Climate, and Society*, 15(1), 159-175, https://doi.org/10.1175/WCAS-D-22-0063.1 [31]

The article has been edited for inclusion in this thesis to remove information already discussed elsewhere. Footnotes indicate where notable amendments have been made to the original article. Minor amendments have also been made to ensure consistent use of terminology within this thesis.

Abstract

It is now widely acknowledged that climate change will have a considerable impact on various aspects of human existence, and this includes happiness and satisfaction with life. This study adds to the existing literature on the contribution of climate to wellbeing by exploring the interaction of various climate variables at the national and local levels while controlling for socio-economic factors. Using climate data covering a 20-year period and

[31] Individual authors' contributions: P Lignier, conceptualisation, design, data analysis and manuscript writing; D Jarvis, project supervision, conceptual guidance, technical guidance, and critical manuscript review; D Grainger: project supervision, technical guidance and critical manuscript review; T Chaiechi, project supervision and critical manuscript review.

demographic data from the HILDA surveys, several OLS models of interaction are developed to test the proposition that climate does influence life satisfaction. Geographically Weighted Regression is then applied to explore how the relationship between explanatory variables and life satisfaction varies across different regions of Australia. I find that annual rainfall, temperature, and sunshine have a small but significant effect on individual life satisfaction. The spatial analysis reveals an elevated level of non-stationarity in the way climate variables impact life satisfaction, suggesting that regional climate type may be a crucial element influencing the relationship. The understanding of this relationship may assist policy makers who develop resilience and adaptation strategies as we face the impacts of climate change.

3.1 Introduction[32]

In a world facing climate change, improving understanding of how climate affects wellbeing is important if policy makers are to develop appropriate adaptation and resilience responses. This study explores the influence of climate factors on the individual wellbeing of people residing within Australia while controlling for the impact of demographic and socio-economic variables. The positive or negative influence of natural environment variables on human wellbeing has been relatively well investigated; the literature that has examined the contribution of weather and climate to LS is relatively more limited.[33]

In this study, I propose alternative LS regression models incorporating climate variables in addition to the demographic and socio-economic factors commonly included in LS regression models. I then conduct a spatial analysis using Geographically Weighted Regression to examine the variations in the model(s) across different regions of Australia. The outcomes from this research can inform predictions about how the anticipated changes in climate are likely to affect wellbeing, and so assist in designing policies to build an appropriate adaptive capacity. An understanding of how contextual climate variables interact with other factors to influence wellbeing will also help in explaining why people move between regions and between countries.

The remainder of the chapter is structured as follows. Section 3.2 reviews the existing literature on climate and LS; Section 3.3 discusses the specific methodology applied to this study. In Section 3.4, I explain how the data was selected and prepared for the purpose of this

[32] Significant content in this section has been removed from the published paper to avoid redundancy of information already included elsewhere in the thesis.

[33] For a critical review of the literature on the influence of natural capital on wellbeing see Jarvis et al. (2023).

research. Section 3.5 lays out the specification of the regression models, while results are presented in Section 3.6. A discussion of the findings follows in Section 3.7; in Section 3.8, findings are summarized, and suggestions are made for further research on this topic.

3.2 Climate, weather, and life satisfaction

Apart from research on climate and LS in the field of economics, a significant body of the broader literature has discussed the effects of weather and climate on humans: physiological effects (e.g., heat related diseases) (Vargas & Magana, 2020); psychological effects (e.g., mood disorders) (Yang et al., 2021; Zander et al., 2019); society effects (e.g., culture, migrations) (Parker, 1995). Economic impacts on activities such as agriculture, tourism, labour productivity, natural disasters management and recovery have also been examined (Chaiechi, 2020; Parsons, 1993).

Investigations of how *weather* conditions at the time of survey impact on LS rating by respondents have led to inconclusive results. Higher precipitation and higher temperature may have a negative effect on reported LS scores (Connolly, 2013), as may recent cloud cover (Barrington-Leigh, 2008); however Levinson (2009) found that precipitation and temperature had a positive effect while Lucas and Lawless (2013) reported little evidence of an association between weather variables and LS judgements. In a longitudinal study conducted over 18 months undertaken in Osaka, Japan, temperature was found to weakly affect happiness while other meteorological variables had no impact (Tsutsui, 2013). In their Australian study, Feddersen et al. (2016) show a positive and significant influence of solar exposure but negative effects of barometric pressure and wind speed on LS ratings. They also note that weather bias is more prominent for cognitively complex questions (such as evaluation of overall LS) and that bias declines with panel experience.

Studies that focused on the influence of *climate*[34] (as opposed to weather) on LS have often used country-level data. Temperature and precipitation variables explain some of the variations in wellbeing between countries; however, the effects are not uniform across seasons or climate types. It seems that a rise in temperature during colder months increases LS, while a similar rise during hotter months has a negative effect (Frijters & Van Praag, 1998; Rehdanz & Maddison, 2005). Likewise, warmer temperatures improve LS for people living in cool climates but lower LS in hot climates (Maddison & Rehdanz, 2011). In a

[34] The difference between weather and climate is discussed in Hulme et al. (2009). See note #20 for further comments on this issue.

single-country study conducted in Ireland, increases in Winter minimum and Summer maximum temperatures are both associated with higher levels of LS (Brereton et al., 2008). On the other hand, a recent Australian study found that heat related stress had no significant impact on either overall LS or momentary happiness (Zander et al., 2019). Precipitation was often determined to be non-significant, however more months with very little rainfall appear to reduce LS (Rehdanz & Maddison, 2005). Drought and risk of drought are also shown to have a negative effect on LS, especially among the poorer section of the population (Berlemann & Eurich, 2021a). In Ireland, increased mean rainfall has a slightly positive effect on LS. According to the authors, this result may be driven by a positive correlation between high rainfall and scenic beauty (Brereton et al., 2008).[35] Also from the Ireland study, wind speed emerges as a significant but negative contributor to LS, and so does surprisingly sunshine duration. But as sunshine duration is negatively associated with rainfall, it is possible that some hidden characteristics of rainfall (frequency, intensity) may bias the results (Brereton et al., 2008).

Many discrete climate variables will have a greater influence on LS when combined, as their individual impacts may be compounded. A study undertaken in Russia shows that strong winds have a significant negative effect on wellbeing in January when associated with cold temperatures (windchill factor); likewise "stickiness" (interaction between high temperature and high humidity) is found to reduce wellbeing (Frijters & Van Praag, 1998). Other evidence suggests that climate variables may also combine with other factors that amplify or moderate their effect on wellbeing. For instance, national wealth qualifies the relationship between temperature and happiness: people living in less temperate countries tend to be happier if they are richer and less happy if they are poorer (Van de Vliert et al., 2004).

The impact of single climate events at specific locations has also been researched: drought (Berlemann & Eurich, 2021a; Caroll et al., 2009), floods (C. J. Fernandez et al., 2019; Luechinger & Raschky, 2009; Sekulova & Van den Bergh, 2016), extreme cold weather (Kraehnert & Fluhrer, 2021), extreme heat (Nitschke et al., 2011) and hurricanes (Ahmadiani & Ferreira, 2021; Calvo et al., 2015). The evidence suggests that beyond the

[35] It should not be concluded from this correlation that high rainfall is necessarily associated with *scenic beauty* although lush green vegetation is generally associated with increased rainfall. In Ireland, regions in the West of the country with high mean rainfall also happen to have spectacular landscapes.

obvious immediate effect on welfare, these extreme weather events were detrimental to the LS of people in the affected regions, often for a prolonged period. It also shows that the mere risk of natural hazards such as hurricane or tornado decreases LS (Berlemann & Eurich, 2021b).

Country-level studies allow the comparison of climate factors in different climatic conditions, but they overlook that the climate is likely to be perceived at a local rather than a national level (Brereton et al., 2008). While the Ireland study addresses this issue, it was conducted in a small country with a relatively homogeneous climate that precludes the analysis of climatic variations between regions. In this chapter, I examine the impact of climate variables on LS in different climate zones of Australia. While the incidence of specific climate factors has been investigated in the US (Berlemann & Eurich, 2021a, 2021b), to my knowledge, this study is the first to analyse the incidence of a wide range of climate factors in a large country since the 1998 Frijters & Van Praag Russia study.

3.3 Methodology

3.3.1 OLS empirical model

Based on the assumption of cardinality of the dependent variable discussed in Chapter 2, I seek to develop an explanatory linear model using the Ordinary Least Square (OLS) technique. The generic form of the model can be written as follows:

$$Y_k = \alpha + \beta' a_k + \gamma' b_k + \delta' c_k + \varepsilon_k \quad k = 1, \ldots \ldots . K$$

where Y_k denotes the average LS score for respondents at location k, a_k denotes a vector of spatial factors representing average demographic conditions for respondents living at location k, b_k denotes a vector of spatial factors representing contextual conditions (socio-economic, environmental) at location k, c_k denotes a vector of spatial factors representing climatic conditions at location k and ε_k is the error term for location k. Possible model bias may be induced by omitted variables, collinearity between variables and heteroscedasticity and will be addressed throughout this chapter.

3.3.2 Choice of spatial scale

As the primary focus of this study is to investigate spatial variations, individual data is aggregated by spatial unit. The spatial scale retained here is the Statistical Area Level 2 (SA2); this choice of spatial scale was justified in Section 2.5.2 of Chapter 2. 2,019 SA2 out of a total of 2,303 are represented in this study, each containing an average of 86 individual responses for each wave. Where the variable is continuous, the mean is calculated for each

SA2. For ordinal and categorical variables (e.g., gender), a proportion is calculated for a particular value (e.g., male).

3.3.3 Geographic Information Systems and Geographically Weighted Regression

The use of a Geographical Information System (GIS) as a tool of investigation seemed appropriate for this study. Within the LS economics literature, examples of studies where a GIS was used include Brereton et al. (2008), Jarvis et al. (2017) and Kubiszewski, Jarvis, et al. (2019). The software used for this study is *ArcGIS-ArcMap* version 10.7.1.

While climate is assumed to be fixed over time, it typically varies across regions; therefore, it is highly likely that specific climate factors will impact LS differently at different geographic locations. In statistical terms, this means that the coefficients of climate variables in LS models are expected to vary depending on geographic location, a phenomenon known as spatial non-stationarity. A technique widely used to investigate how spatial non-stationarity affects the relationship between variables across different locations is Geographically Weighted Regression (GWR) (Fotheringham et al., 2002). Within the framework of a global model, GWR allows the estimation of the local relationship between contributing variables and the dependent variable (LS). For this purpose, it estimates the value of regression coefficients at each location using a matrix of variable values in the vicinity of the core location (Wheeler & Tiefelsdorf, 2005). While GWR is a very useful tool, the presence of local multicollinearity between variables can impair the model's explanatory power and coefficient estimation (Fotheringham & Oshan, 2017; Wheeler & Tiefelsdorf, 2005). Prior to undertaking GWR, it is essential to ensure that the overall level of spatial non-stationarity in the OLS model warrants the exploration of spatial heterogeneity in the relationship between variables and to check for possible spatial autocorrelation. Spatial non-stationarity is measured by the Koenker Studentised Breusch Pagan (BP) statistic and spatial autocorrelation by the Global Moran's Index.

The OLS empirical model adapted for estimation through GWR is defined as follows:

$$Y_k = \alpha_k + \sum_{i=1}^{p} \beta_{i,k} x_{i.k} + \varepsilon_k, \quad i = 1, \dots \dots I; \;\; k = 1, \dots \dots K$$

where Y_k denotes the average LS score at location k, α_k denotes the intercept at location k, x_{ik} is the value of the i^{th} explanatory variable at location k , β_{ik} denotes the coefficient for the i^{th} variable at location k, and ε_k is the error term at location k.

3.4 Data[36]

3.4.1 Data sources

The source for LS and personal demographic data used in this study is the HILDA survey (Melbourne Institute, 2022). The data was pooled from the ten latest waves (Waves 11 to 20) of the survey spanning the period 2011-2020. Socio-demographic data is mostly derived from individual respondents' responses except for household income and housing status compiled by households. The data for this study includes responses from 174,857 individual respondents linked to 102,224 households.

Climate data including rainfall, temperature, solar exposure, humidity, and wind were obtained from The Australian Bureau of Meteorology (BOM) (Bureau of Meteorology, 2013). Weather observations cover the period 2000-2020 for temperature and rainfall, and 2000-2017 for solar exposure, humidity, and wind. By averaging weather observations over a relatively long period of time, I assume that the resulting data represents a climate trend that is fixed over time (NOAA, 2021). Contextual socio-economic indicators were sourced from the Australian Bureau of Statistics (ABS), in particular, the ABS Socio-Economic Index For Australia (SEIFA) from the 2016 census (Australian Bureau of Statistics, 2018). Finally, the Normalised Difference Vegetation Index (NDVI) available from BOM was used as a proxy for natural capital (Bureau of Meteorology, 2021).

An assessment of the sample representativeness of socio-demographic variables was conducted by comparing sample means to the 2016 census data. The results (Table 3-1) show that overall, the characteristics in the sample were representative of the socio-demographic attributes of the general Australian population. However, respondents in the sample had, on average, a higher income and were slightly older. The percentage of respondents who own their house (outright or with a mortgage) was also markedly lower than the national average.

[36] Some content placed in the appendix of the published article have been integrated into the main body of this section.

Table 3-1 Sample representativeness

Variable	Sample mean	Australia average*
Proportion of males	47.2%	49.3%
Mean age	42.6 years	38 years
Proportion of unemployed	4.84%	6.9%
Proportion identifying as ATSI	3.96%	2.8%
Proportion of people in a relationship	56.4%	58.1%
Household income (annual)	$100,146	$74,776
Proportion who own their house	49.0%	65.5%
Proportion with a university degree	22.5%	22.0%

* Source: Australian Bureau of Statistics, 2016 Census QuickStat, https://quickstats.censusdata.abs.gov.au/census_services/getproduct/census/2016/quickstat/318?opendocument

3.4.2 Data preparation

3.4.2.1 Selection of socio-demographic and contextual variables

The selection of personal demographic and economic variables was in line with the factors determined to be significant in previous LS studies (Ambrey & Fleming, 2014; Kubiszewski, Jarvis, et al., 2019). The standard deviation of LS in each area (LSSD) was included as a key explanatory variable pursuing evidence from previous LS studies showing that heterogeneity in levels of happiness within a region itself impacts people's happiness (Kubiszewski, Zakariyya, et al., 2019).

The socio-economic environment of each SA2 can be described by the decile rankings for the four SEIFA indexes computed by the ABS: Relative Social disadvantage (IRSD), Relative Social Advantage and disadvantage (IRSAD), Economic Resources (IER), Education and Occupation (IEO) (Australian Bureau of Statistics, 2018). The SEIFA deciles were not directly incorporated into the model because of their high level of multicollinearity[37]; instead, I used variables representing the interaction between personal variables and the socio-economic context: average household income × SEIFA decile for IER (relative income) and proportion with higher education × SEIFA decile for IEO (relative education status). This is justified on the empirical ground that relative income (and to some extent relative education status) matters more to individual happiness than absolute levels of income (Blanchflower & Oswald, 2004; Frey & Stutzer, 2000; Shields et al., 2009).

[37] All SEIFA indexes are based on similar underlying variables.

3.4.2.2 Selections of climate variables

Among the six categories of climate variables temperature, precipitation, cloud cover/sunshine, humidity, wind and atmospheric pressure (San-Gil et al., 1991), the first five categories are represented in this study. Atmospheric pressure may be of interest as an instant weather variable (see Feddersen et al. (2016)); however, considering its high variability, it is not believed to be relevant as a climate variable (Keller et al., 2005).

Previous research provided guidance for selecting appropriate climate variables. The model should include variables representing each climate characteristic: rainfall, temperature, sunshine, humidity and wind (Brereton et al., 2008). Multicollinearity should be minimised by avoiding the simultaneous inclusion of variables with a high degree of correlation. Extreme values are often more relevant than averages as they are more easily perceived (Cushing, 1987; Van de Vliert et al., 2004). Cross-over variables that reflect the recurrence of specific weather conditions should be introduced: e.g., windchill factor or stickiness (Frijters & Van Praag, 1998). The model specification should have an overall consistency: i.e., include extreme cold and extreme hot, rather than extreme cold and average maximum. Where appropriate, the likelihood of non-linear relationship should be addressed by including variables either in squared (Maddison & Rehdanz, 2011; Van de Vliert et al., 2004) or log form (Frijters & Van Praag, 1998).

Average climate values for each spatial unit (SA2 in this study) were determined from each station average data. In Geographic Information System datatype standards, station data are in point format, so they needed to be converted into polygon datatype by using the *Thiessen Polygon* mapping tool available from *ArcGIS*. Each polygon was then intersected with the geographic SA2s allowing the calculation of an average for the spatial unit based on area.

3.4.2.3 Dimension reduction

The selection of relevant climate variables is a delicate process that can lead to some important variables being omitted. Rather than trying to select variables based on heuristics, an alternative approach is to adopt a dimension reduction technique allowing the computation of summary variables based on statistical criteria (Frijters & Van Praag, 1998). Principal Component Analysis (PCA) available in *SPSS Version 26*, was used as a method of variable reduction. Variables that can be potentially summarised by principal factors must have a degree of correlation between them; however, the degree of correlation must not exceed

R=0.8 as this would create multicollinearity issues. Adequacy of sampling is measured by the Kaiser-Meyer Olkin (KMO) index and must be > 0.6 as well as the Bartlett's test of sphericity which must be highly significant ($p<0.01$).[38] To minimise the multicollinearity problems, climate variables were categorised into three separate perception constructs: temperature, rainfall, and sunshine. Stickiness and windchill have been previously defined as cross-factors between two specific variables and therefore were excluded from the pool of candidate variables for factor reduction. A trial-and-error process was initiated to try to determine the pool of variables that would lead to meaningful principal components with the best fit.

Table 3-2: Principal Component Analysis: Structure of climate factor components

Rotated Component matrix [a]		
	Component	
	Climate factor 1 (hot & dry)	**Climate factor 2 (wet & warm)**
Rainfall Wettest Month	-0.004	0.932
No of Months < 30mm	0.896	-0.058
MAX temp hottest month	0.851	0.249
Annual sunshine hours	0.825	0.394
Heating degree Months	-0.412	-0.804
	Standardised factors	
	Climate Factor 1	**Climate Factor 2**
Minimum score	-2.951	-2.458
Maximum score	3.804	4.986
Mean value	0.000	0.000
Std Deviation	1.000	1.000

a Rotation method: Varimax with Kaiser Normalisation. Rotation converged with three iterations.

The optimal result identified a set of five variables categorised into *two* principal components. The corresponding rotated component matrix showing the principal constituents and respective contributing variables is presented in Table 3-2. Kaiser-Meyer Olkin for this model is 0.703 and the Bartlett Test of Sphericity is highly significant (99%). The two components explain 82.27 % of the total variance of the constituent variables. Variables related to hot temperature, prolonged dry weather and sunshine hours load strongly and positively into Component 1, thereafter labelled 'Climate Factor 1' representing hot, dry, and

[38] For further information about these measures, see: https://statistics.laerd.com/spss-tutorials/principal-components-analysis-pca-using-spss-statistics.php

sunny climate features. The main variable represented in Component 2 is 'rainfall in wettest month' that loads strongly and positively; however, Heating Degree Months (a proxy for extreme cold temperatures) also loads strongly but negatively. This composite variable thereafter labelled 'Climate Factor 2' represents both wet and warm climate features. Standardised scores for each component (bottom part of Table 3-2) were generated by SPSS using the 'regression method'.

3.5 Specification of regression models

A dataset containing 2,006 valid observations is analysed using five separate OLS regression models (hereafter referred to as Models 1 to 5). Each model examines how climate factors in different forms contribute to LS, while socio-demographic variables remain the same. Model specifications are described in Table 3-3.

Table 3-3: Explanatory variables used in the specifications for Models 1-5

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Socio-demographic	LSSD, age squared, gender, marital status, health status, household income, house ownership, education status, relative income, relative education status, NDVI				
Rainfall	Rainfall in driest month, Rainfall in wettest month	Rainfall in driest month, Rainfall in wettest month	Months < 30 mm, Months ≥100 mm	Annual rainfall + square	
Temperature	Max hottest month Min coldest month	Heating Degree Months Cooling degree Months	Days > 30° Days < 5°	ln mean temp. ln diff. mean temp hottest /coldest month	
Sunshine	Annual sun hours	Annual sun hours		ln annual sun hours	
Cross-factors	Stickiness: (humid. x av. max temp), Windchill: (windspeed × av. min temp)	Stickiness: (humid. x av. max temp), Windchill: (windspeed × av. min temp)	Days humid. > 75%	Stickiness: (ln humid. x ln av. max temp), Windchill: (ln windspeed × ln av. min temp)	Stickiness: (ln humid. x ln av. max temp), Windchill: (ln windspeed × ln av. min temp)
Composite factors					Climate fact 1 Climate fact 2

Model 1 is based on the premise that extreme climate features influence LS more than average measures and partly replicates the first model specification in Rehdanz and Maddison (2005). Model 2 relies on the concept of Heating Degrees and Cooling Degrees as a measure of the discomfort created by extreme temperatures. Following the methodology used by Maddison and Rehdanz (2011), the model includes Heating Degree Months (HDM) and

Cooling Degree Months (CDM). Instead of the North American baseline of 65°F (18.3°C), this study adopts a baseline of 20°C that better reflects the higher average temperatures in Australia. Model 3 uses counts rather than the actual climate measures. The rationale for this approach is that people experience the weather in terms of its duration as well as its intensity (Rehdanz & Maddison, 2005).

The use of descriptive climate variables in their primary form implies the assumption of a linear interaction between the climate factor and LS. This assumption can be relaxed to allow for the possibility of non-linear relationships by transforming the explanatory variables (Frijters & Van Praag, 1998; Maddison & Bigano, 2003). Different transformations were considered: square value; primary value + square value; natural log value, a combination of the above. After several iterations, a combination of primary values, square values and log values of various climate factors were included in Model 4. Finally, Model 5 includes the two climate factors determined through the PCA process described in Section 3.4.2.3 as well two cross-over factors representing stickiness and windchill.

Prior to estimating OLS regressions, initial checks were conducted regarding collinearity and behaviour of residuals. Scatter plots did not show convincing patterns of collinearity between dependent (DV) and independent variables (IV). Correlations between the DV and individual IVs were usually very low ($R<0.1$). There was no excessive collinearity between IVs. Residuals plots indicate that the assumption of homoscedasticity holds. Histograms and normal probability plots indicate that the assumption of normality in the distribution of residuals holds. In short, the Gauss Markov conditions necessary for properly interpreting the series of OLS held.

3.6 Results

3.6.1 OLS regression results

All five OLS models were estimated in *SPSS*. For each model, two versions were assessed: one version used the specifications described in Table 3-3, and the second version also included dummy variables representing each of the eight Australian states and territories. A summary of the regression results for the second version is presented in Table 3-4.

A preliminary model estimation without climate variables indicates that socio-demographic factors explain 21% of the variance in LS. The inclusion of climate variables increases the explanatory power of the model (measured by adjusted R^2) by a value ranging

from 0.010 to 0.012, i.e., variations in climate variables contribute 1% -1.2% to the total variance in LS.

When state/territory dummy variables are incorporated, adjusted R^2 rises by a further 0.08 to 0.13. Models 1-3 have an adjusted R^2= 0.227, Model 4 slightly higher at 0.229 and Model 5 slightly lower at 0.219.

Demographic and socio-economic variables behave consistently across the models with similar coefficients and levels of significance. This suggests structural stability and robustness in the relationship between these variables and LS. All variables contribute positively to LS except 'being male' and 'having a university degree' The standard deviation of LS (LSSD) has a significantly negative coefficient. Relative education status is a significantly positive socio-economic contributor to LS, relative income is non-significant when dummy location variables are included; the natural capital proxy variable (NDVI) is not significant except in Model 5.

Variables representing extreme rainfall values are significant (Models 1 and 2). Count variables for both dry and wet months are significant (Model 3). All factors have positive coefficients except for rainfall in the driest month. Average rainfall in quadratic form ($x + \frac{1}{1000}x^2$) is significant (Model 4) with a negative coefficient. The results for temperature variables are inconclusive: minimum in the coldest month is significantly negative (Model 1), but both HDM and CDM are significantly positive (Model 2), while 'number of days over 30° C' is significantly positive (Model 3). The natural log of 'average mean temperature,' and 'difference in temperature between coldest and hottest month' are both significant and negative (Model 4). The natural log of sunshine hours is significantly positive. Stickiness (positive) and windchill (negative) are only significant when calculated from log values (Model 4). Climate factor 1 (hot & dry) is found to be significant and positive, but Climate factor 2 (wet & warm) is not (Model 5).

Coefficients for the state and territory dummy variables are generally non- significant except for Western Australia, which was significantly negative across all five models. This would suggest a different pattern of relationship between IVs and DV in that state.

Table 3-4: OLS Regression coefficients for Models 1-5 (with state dummies)

		Model 1	Model 2	Model 3	Model 4	Model 5
n		2,006	2,006	2,006	2,006	2,006
Model Fit	Adjusted R^2	0.227	0.227	0.227	0.229	0.219
Variables		Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
	LS Std Deviation	-0.330***	-0.337***	-0.315***	-0.328***	-0.323***
Micro-demographic	Gender	-0.253***	-0.250***	-0.255***	-0.250***	-0.252***
	Age squared	0.017***	0.017***	0.016***	0.016***	0.017***
	Marital status	0.160***	0.160***	0.149***	0.154***	0.160***
	Income	0.001***	0.001***	0.001**	0.001**	0.001**
	Housing status	0.144***	0.137***	0.158***	0.152***	0.155***
	Health status	0.720***	0.711***	0.728***	0.711***	0.725***
	Education status	-0.676***	-0.651***	-0.676***	-0.657***	-0.672***
Socio-economic	Relative income	-0.000	-0.000	-0.000	-0.000	-0.000
	Relat. educ. status	0.063***	0.059***	0.064***	0.063***	0.061***
Nat. Capital	NDVI average	0.044	0.035	0.170	0.110	0.302**
Rainfall	Rainfall driest m.	-0.003**	-0.004***			
	Rainfall wettest m	0.001***	0.001***			
	Months <30 mm			0.024***		
	Months >100 mm			0.023***		
	Annual rainfall				-0.001***	
	Annual rain (sq.)				0.000***	
Temperature	Max. hottest m.	-0.003				
	Min. coldest m.	-0.024***				
	Heating DM		0.001*			
	Cooling DM		0.002**			
	Days min <5°			0.000		
	Days Max > 30°			0.001***		
	Mean temp (ln)				-0.824***	
	Diff mean temp (ln)				-0.193**	
Sunshine	Annual sun hrs	0.000	0.000*			
	Annual sun hrs (ln)				0.498***	
Stickiness	humidity × hot	-0.000*	-0.000*			
	Days hum. > 75%			-0.000		
	ln humid × ln hot				0.098**	-0.024
Windchill	Windspeed × cold	-0.005	-0.005			
	ln wind × ln cold				-0.086*	0.025
Climate Fact 1						0.049**
Climate Fact 2						0.034
State/Territ. dummy	NSW	0.038	0.017	0.047	0.024	0.068*
	Vic	0.043	-0.016	0.052	-0.049	0.083
	QLD	Excl.	Excl.	Excl.	Excl.	Excl.
	SA	0.076	-0.041	0.048	-0.045	0.096
	WA	-0.176***	-0.290***	-0.184***	-0.206***	-0.126***
	Tas	0.109	0.047	0.044	0.008	0.222**
	NT	-0.042	-0.020	-0.003	-0.001	0.014
	ACT	-0.130*	-0.154*	-0.026	-0.153**	0.032

Coefficient significance levels: *** p <0.01; ** p <0.05; * p<0.1

3.6.2 Geographic investigation results

3.6.2.1 General evaluation

The estimation of the five global OLS models in *ArcGIS* shows similar results to the SPSS regressions.[39] For all models, the Koenker BP statistic is highly significant, indicating the presence of non-stationarity in the relationship between variables, thus warranting a GWR investigation. The Global Moran's Index is found to be significant in three out of five models implying that residuals may not be randomly spatially distributed (spatial autocorrelation). Clustering of residuals tends to occur in remote statistical areas where the number of respondents is small; hence averages in those areas are more sensitive to extreme values.

Besides autocorrelation, multicollinearity between factors is another problem that can plague GWR, in particular local multicollinearity that is difficult to detect (Wheeler & Tiefelsdorf, 2005). In *ArcGIS*, multicollinearity (global or local) causes the model to fail. Bearing in mind those constraints, successive trial-and-error estimations led to the identification of a GWR model that is a simplified version of Model 5 with ten explanatory variables comprising eight demographic variables and the two composite climate factors. A comparison between the OLS and GWR models is shown in Table 3-5. The overall model fit for the GWR model (Adjusted $R^2 = 0.254$; the mean value of local $R^2 = 0.235$) is markedly improved from the OLS model with the same specification ($R^2 = 0.192$).[40] The mean value of local coefficients for the explanatory variables were close to the OLS coefficients in the original Model 5. Only education status was markedly different presumably because relative education status was dropped in the GWR model.

[39] When repeating the OLS models within *ArcGIS* the state/ territory dummy variables were excluded, as due to the spatial basis of the software, the inclusion of categorical variables representing locations is not recommended. *ArcGIS* also calculates the corrected Akaike Information Criteria (AIC), a related measure that also evaluates model fitness. For more information on the Akaike Information Criterion see: https://www.sciencedirect.com/topics/social-sciences/akaike-information-criterion .

[40] AIC also improved from 2,670 (OLS model) to 2,538 for the GWR model.

Table 3-5: Comparison of regression results between OLS and GWR models

	Original Model 5 (no state dummy)	**OLS Model (same specification)**	**GWR (mean values)**
Adjusted R2	0.211	0.192	Local R^2: 0.235
Coefficients:			
LS Stand. deviation	-0.332*	-0.318*	-0.303#
Gender	-0.234*	-0.210*	-0.181
Age Squared	0.016*	0.015*	0.0155#
Marital status	0.161*	0.177*	0.185#
Household Income	0.001*	0.001*	0.001
Housing status	0.157*	0.176*	0.169#
Health status	0.690*	0.650*	0.610#
Education status	-0.653*	-0.243*	-0.147
Relative income	-0.000*	N/A	N/A
Relative education	0.058*	N/A	N/A
NDVI	0.371*	N/A	N/A
Climate Factor 1	0.011	-0.020	0.027
Climate Factor 2	0.012	-0.004	-0.001
"Stickiness" (ln)	-0.036	N/A	N/A
Windchill (ln)	0.022	N/A	N/A

*OLS Coefficient significant at 90% level

#>80% of local GWR coefficients are significant at 90% level

3.6.2.2 Life satisfaction and socio-demographic variables

Mean LS scores by SA3[41] average 7.9, ranging from a minimum of 6.2 to a maximum of 8.6 (Figure 1). The relationship between the mean LS score and the standard deviation of individual LS scores (LSSD) within the area is always negative, with the coefficient ranging from -0.393 to -0.053, and strong negative values in southeast regions and the southern part of Western Australia (WA).

'Having no long-term health condition' is always significantly and positively related to LS and almost always the largest contributor. The factor is particularly strong in northern Australia and in outback areas. Age (squared) is also a significant positive factor but weaker

[41] To make interpretation easier, the results were aggregated at SA3 levels. Note that this is an aggregation for presentation purposes only; this is different from conducting a regression analysis at SA3 level. 331 out of a total 340 spatial SA3 statistical areas were represented in the sample. SA3 often closely align with large urban local government areas. In the country they represent areas that have distinct identity and socio-economic characteristics (ABS, 2016).

than health. The strongest impact of age on LS is in western and central Australia. 'Being male' is overwhelmingly a negative contributor to LS, particularly so in WA and South Australia. 'Being in a relationship' is a significantly positive contributor in a broad arc spanning from South Australia to central Queensland, an area comprising about 85% of the Australian population.

Household income is a small but significant contributor to LS in most of New South Wales (NSW), Queensland and Tasmania, in the areas to the east of the city of Melbourne as well as the far northern and far southern WA. House ownership is a significantly positive contributor in NSW, Victoria, Queensland, and most of WA. 'Having a university degree' is a negative contributor to LS everywhere except for most of WA where it is not significant.

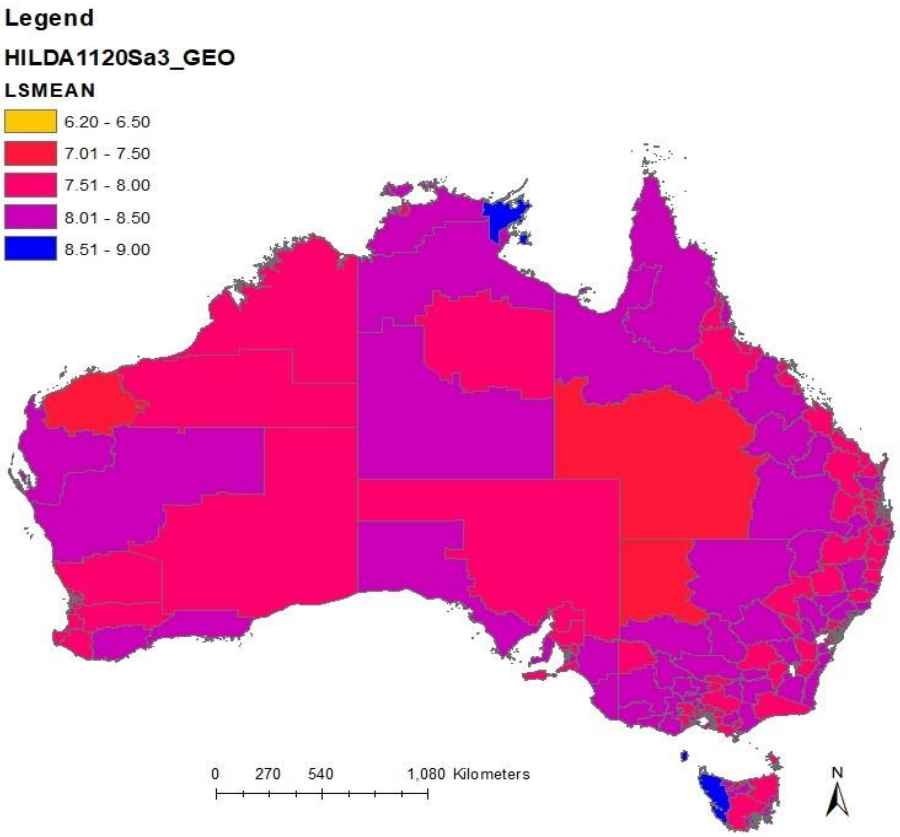

Figure 3-1: Mean LS scores aggregated by SA3, where LS score of 10 represents the highest possible level of satisfaction with life overall, and 0 represents the least

3.6.2.3 Climate variables

Climate Factor 1 is a composite factor that scores positively in regions with a hot, dry, and sunny climate and negatively in cool and cloudy areas (Figure 3-2). Climate Factor 1 is a

significantly *negative* contributor to LS in the hot regions of central Australia and northern WA where scores are highly positive. Conversely, it is a significantly *positive* contributor to LS in southeastern regions where the factor is neutral (low positive values) reflecting more temperate conditions (Figures 3-3 and 3-4).

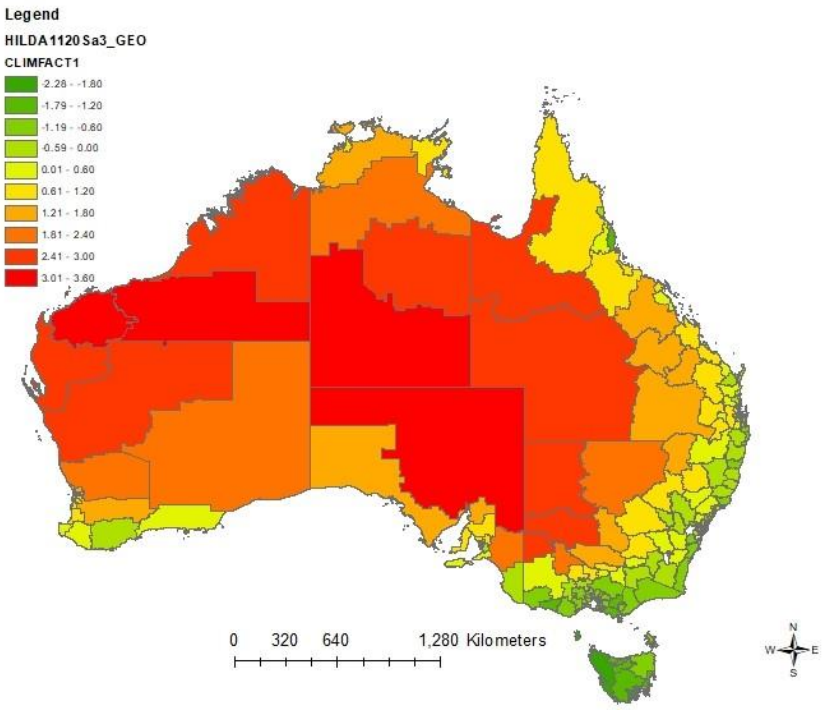

Figure 3-2: Scores for Climate Factor 1 by SA3, higher scores indicating hotter, drier, and sunnier regions, and lower scores indicating cooler and cloudier regions

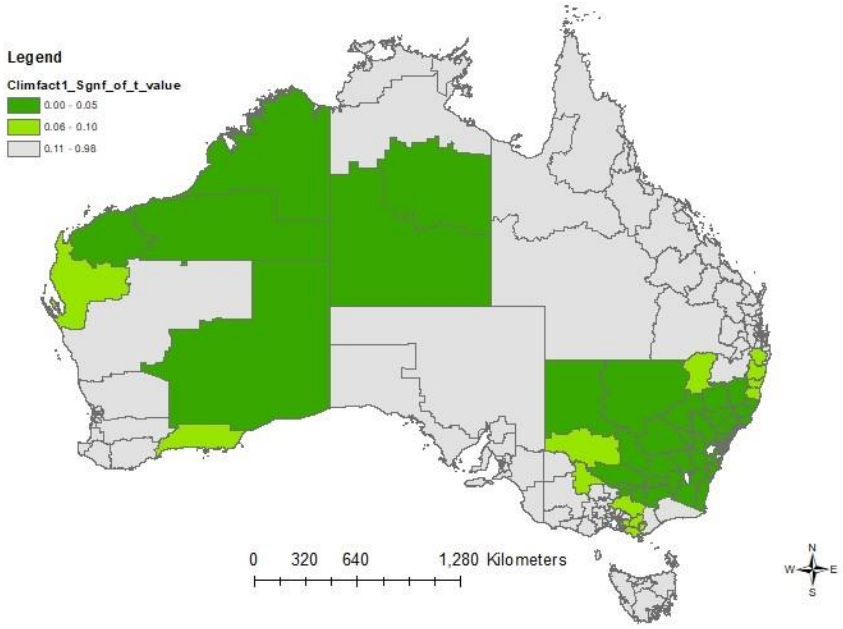

Figure 3-3: Significance of local coefficient for Climate Factor 1 aggregated by SA3

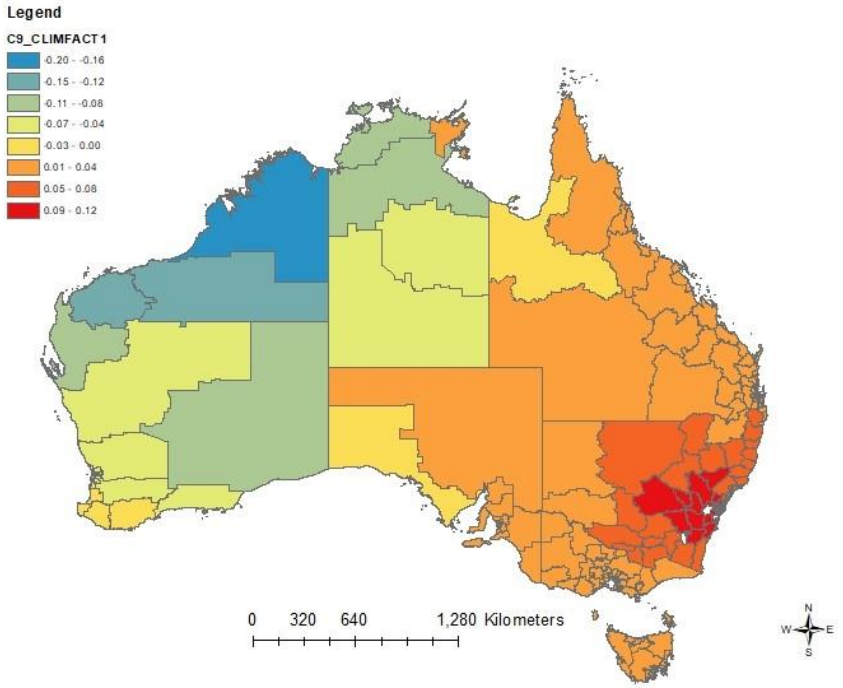

Figure 3-4: Local regression coefficient values for Climate Factor 1 aggregated by SA3

Rainfall during wet months is the main constituent variable in Climate Factor 2, however Heating Degree Month (a proxy for cold temperatures) is also a significant *negative* constituent. So, regions featuring both a pronounced wet season and warm winters will score positively, while regions with a low rainfall peak and cool to cold winters have negative scores (Figure 3-5). Climate Factor 2 was a significantly *positive* contributor to LS in tropical North Queensland with warm winters and pronounced wet season in summer. Conversely, it was a significantly *negative* contributor to LS in southern regions (South Australia, Western NSW, Victoria, and Tasmania) that experience low or moderate rainfall in summer and cool to cold winters (Figures 3-6 and 3-7).

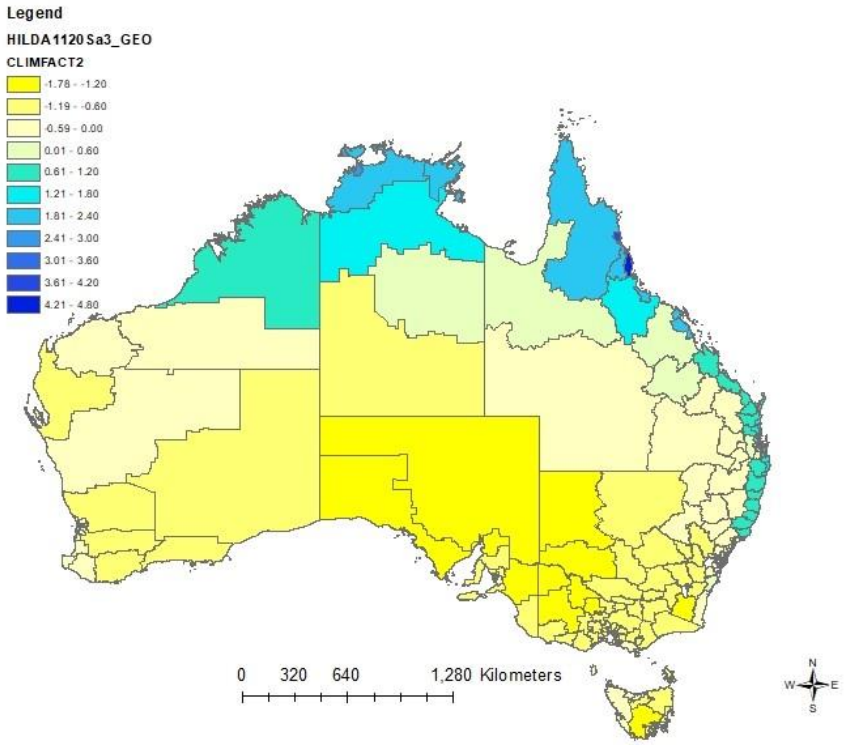

Figure 3-5: Scores for Climate Factor 2 by SA3, with higher scores indicating regions with wetter and warmer climates, lower scores indicating drier and cooler climates

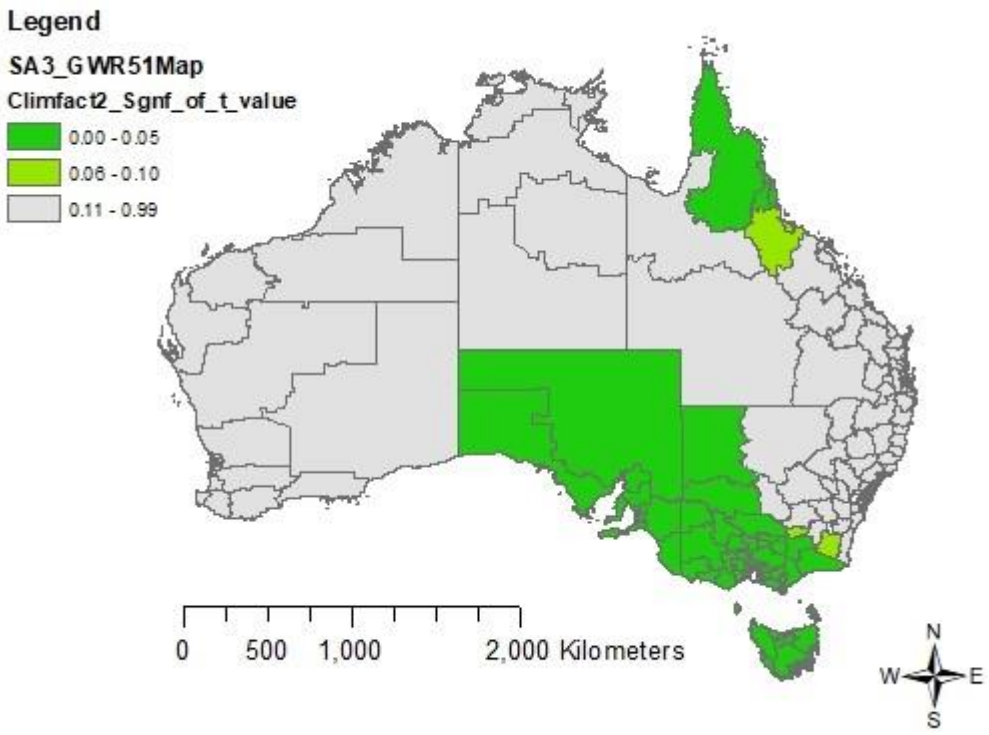

Figure 3-6: Significance of local coefficient for Climate Factor 2 aggregated by SA3

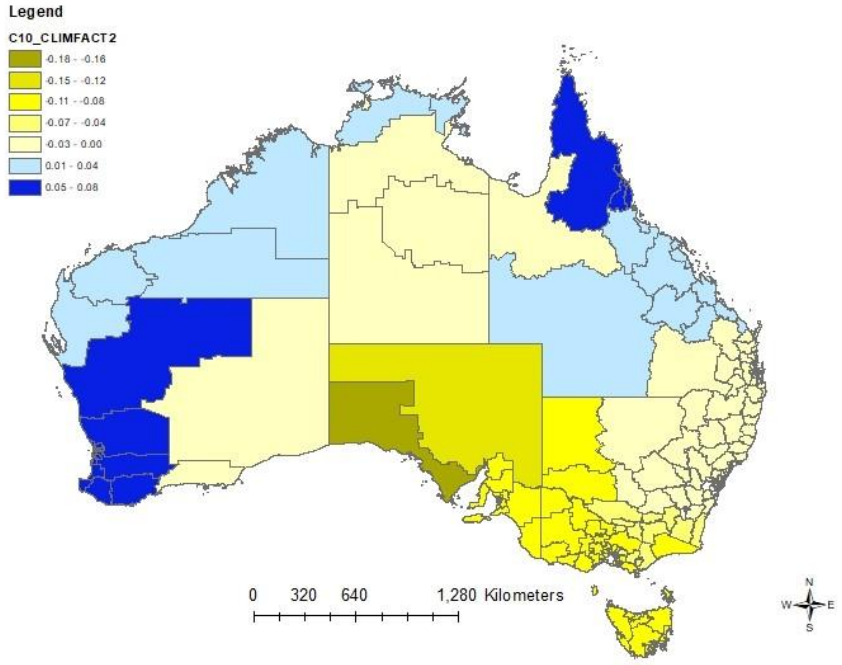

Figure 3-7: Local regression coefficient values for Climate Factor 2 aggregated by SA3

3.7 Discussion

There are significant spatial variations in mean LS scores across Australia, supporting findings from previous research (Kubiszewski, Jarvis, et al., 2019). The distribution of mean LS scores reveals a general pattern where LS is higher in regional areas than in metropolitan areas, a fact also noted by Ambrey and Fleming (2014). Some caution needs to be exercised in interpreting this result because of the small number of observations in some remote areas. The coefficient for the LSSD variable is significantly negative across all areas, implying that mean LS was lower in areas with greater heterogeneity in LS scores; this is in line with the conclusions in Kubiszewski, Jarvis, et al. (2019).

The strength of the relationship (measured by local R^2) between contributing factors and LS varies significantly between regions. While R^2 values range between 0.20 and 0.25 in most areas of eastern and southern Australia, they rise to around 0.30 in the top end of the Northern Territory and the Kimberley (northern WA) and to well above 0.40 in southwest WA. Kubiszewski, Jarvis, et al. (2019) had comparable results with an even wider range of variation (from 0.12 to 0.78). Overall, LS explanatory models for WA tend to deviate from the general pattern in terms of explanatory power and regression coefficients.[42] This begs the questions: *Are there confounding variables that impact on the way socio-demographic and climate variables interact while contributing to LS? Is there a possibility of reverse causality where for instance LS impacts on the way people perceive the climate?* A Western Australia specific study may shed some light on why factors in this region behave differently compared to other regions of Australia. The remainder of this discussion is focused on climate factors.

The global OLS regression models show a small but significant overall contribution of climate variables to LS: low rainfall and high temperatures are both negative contributors, in line with previous findings (Brereton et al., 2008; Rehdanz & Maddison, 2005). There is also some indication from the results in Model 4 that the relationship between climate variables and LS may not be linear, a conclusion also reached by Frijters and Van Praag (1998) and Van de Vliert et al. (2004).

[42] An OLS model with the same specifications as the GWR model was estimated on WA data alone. The Variance Inflation Factors (VIF) were all <2, ruling out multi-collinearity as the source of endogeneity at least at the global level. Thus, the most probable cause of endogeneity appeared to be either a missing variable or reverse causality. Reverse causality in LS models is discussed in Frijters and Beatton (2012).

Model 4 showed a very promising configuration between climate variables and LS; regrettably, local multi-collinearity issues prevented further GWR analysis for that model. Another limitation is that data from ten consecutive HILDA surveys were pooled together and that responses collected at different points in time were treated as contemporaneous. It also means that the data includes responses from individuals who have participated in multiple surveys. This could bias results in rural areas where the total number of responses is relatively low.

The GWR analysis confirms that the impact of climate factors on LS is generally small and patchy across Australia. The spatial distribution of coefficients for Climate Factor 1 suggests that where the climate is hot, 'hotter' impacts negatively on LS, however, a rise in temperature in milder climates has a positive effect corroborating previous results from Rehdanz and Maddison (2005). Excessive heat in tropical cities can be exacerbated by the heat island phenomenon that may bring daytime temperatures to over 45°C (Chaiechi & Tavares, 2019). This is particularly concerning given that the negative effects of extreme heat on mortality and morbidity have been abundantly documented (Hondula & Barnett, 2014; Kovats & Hajat, 2008; Nitschke et al., 2011). Excessive heat has also been shown to be the third most important motivation behind the intention to leave a tropical city in Australia (Zander & Garnett, 2020). The spatial analysis for Climate Factor 2 indicates that in North Queensland, the wet and warm climate has a positive influence on LS. It is worth noting that in the Kimberley region of WA and the top end of the Northern Territory, regions with a similar tropical climate, the coefficient for Climate Factor 2 is not significant. This could be linked to the fact that whereas rainfall in tropical North Queensland is reliable year-round, it is far more erratic (and sometimes catastrophic) in other northern regions. Conversely, Climate Factor 2 is a negative contributor to LS in regions where it has negative values (low peak rainfall, cold temperatures): it is not clear whether the cold temperatures, the lack of rain or the combination of both have the most negative effect on LS. Interestingly, the coefficient for Factor 2 has significant but weak negative values in regions where temperatures are generally cool, and rainfall is moderate (Tasmania and Victoria) but strong negative values in areas with long dry periods and experiencing cold temperatures (South Australia and southwestern NSW). These results appear to support earlier conclusions that drought and risk of drought decrease happiness (Berlemann & Eurich, 2021a), particularly in farming areas (Caroll et al., 2009) while higher and reliable rainfall has a positive impact on LS (Brereton et al., 2008).

A possible limitation to the GWR estimation conducted in this study is that the use of climate factors determined through the PCA process may have led to important climate variables being omitted. A total of five variables representing, hot and cold temperatures, rainfall and sunshine contribute to the composite factors used in the GWR regression, however other variables such as windiness and humidity are not included.

3.8 Conclusion

It transpires from this study that temperature, precipitation, and sunshine likely influence individual LS to some degree, while the effect of other climate variables such as wind speed and humidity is limited. The spatial analysis reveals that for people who live in a hot and dry area, more heat and drought is associated with lower individual LS. This finding doesn't bode well for the future if the climate does become hotter and droughts more frequent (IPCC, 2022). A possible challenge arising from these results is to build the resilience and adaptive capacity of people in affected communities so that climate change has a less adverse impact on their LS. Current climate change strategies at either federal (Australian Government, 2021) or state (Queensland Government, 2017) level make a number of strategic recommendations about how to adapt to the effects of climate change. However, while economic costs are abundantly discussed, there are few references to the consequences of these changes on individual wellbeing. Further research on this issue, such as this study, will help inform future policy initiatives.

The outcomes from this study form the basis of an agenda for future research about the contribution of climate factors to LS. Firstly, further research is needed to explore the importance of contextual climate in shaping the relationship between specific climate variables and LS. This could be achieved by comparing relationship patterns within contrasting climates (e.g., temperate, and tropical climates). Secondly, spatial differences identified in this study suggest that people may perceive climate in diverse ways depending on their environment and their circumstances. This begs the questions: *How do people perceive the climate in their immediate area and how does this perception relate to both actual climate conditions and LS? Is individual perception of climate conditions influenced by specific factors such as occupation, outdoor activity, and level of engagement with nature?* Finally, additional data from rural and remote areas with diverse climates would help our understanding of the spatial variations in LS explanatory models.

Chapter 4 Spatial heterogeneity and subjective wellbeing: exploring the role of social capital in metropolitan areas using multilevel modelling

In this chapter, I address Research Objective #2 identified in Chapter 1 and conduct a systematic analysis of the impact of multiple dimensions of social capital on subjective wellbeing within the context of metropolitan neighbourhoods. This study is particularly innovative in its adoption of multilevel modelling to analyse the interaction between various levels of influence of social capital variables. The analysis confirms the influence of social capital variables on LS at an individual level and reveals some degree of interaction between individual and contextual levels for social engagement and community.

This chapter is based on an article published in the *Journal of Happiness Studies* in May 2024. The article's citation is: Lignier P., Jarvis D., Grainger D., Chaiechi T., 2024, 'Spatial heterogeneity and subjective wellbeing: exploring the role of social capital in metropolitan areas using multilevel modelling' Journal of Happiness Studies, 25:52, https://doi.org/10.1007/s10902-024-00765-4 [43]

The submitted manuscript has been edited for inclusion in this thesis to remove information already discussed elsewhere. Footnotes indicate where notable amendments have been made to the original article. Minor amendments have also been made to ensure consistent use of terminology within this thesis.

Abstract

The role of social capital, the social networks that influence human wellbeing has been explored by empirical research in the US and Europe, however no study so far has undertaken a systematic investigation of the impact of various dimensions of social capital in metropolitan areas. Addressing this gap in knowledge can have practical and policy-oriented implications by contributing to more informed decision-making processes in metro areas, better targeted interventions and ultimately an improved quality of life for residents. This study adopts a multi-level modelling approach to investigate life satisfaction and social

[43] Individual authors' contributions: P Lignier, conceptualisation, design, data analysis and manuscript writing; D Jarvis, project supervision, conceptual guidance and critical manuscript review; D Grainger: project supervision, technical guidance and critical manuscript review; T Chaiechi, project supervision and critical manuscript review.

capital heterogeneity within metropolitan areas in Australia. The dataset was collected by the HILDA survey and includes almost 4,000 individual respondents. The results show that social trust, social engagement and connection, and a psychological sense of community measured at an individual level have a strong positive influence on individual life satisfaction. Conversely negative individual perceptions about neighbourhood criminality and shabbiness are associated with a lower level of life satisfaction. The application of a model using random slope coefficients for social capital variables suggests that most of the spatial heterogeneity between census districts is explained by between-individual (compositional) variations, rather than contextual differences. Only social connection and engagement appeared to have a distinctive contextual influence. These findings confirm the importance of social inclusion in enhancing wellbeing for everyone and may inform social policy on how to promote social networks in urban areas by all levels of government.

4.1 Introduction[44]

Many subjective wellbeing studies incorporate contextual factors among the explanatory variables in the LS regression model. These include variables such socio-economic disadvantage or income inequality (Alesina et al., 2004; Kubiszewski, Zakariyya, et al., 2019; Oishi et al., 2011), environmental factors (Bertram & Rehdanz, 2015; Kubiszewski, Jarvis, et al., 2019) and climate variables (Brereton et al., 2008; Lignier et al., 2023). However, much of this empirical research ignored the various levels of interaction between contributors and wellbeing and thus risk potential endogeneity, i.e., some factors influence LS at an individual (age, education) or household level (income, house ownership), while other are macro-level factors impacting at a neighbourhood or regional level. Research that used a multilevel analysis approach to examine those different levels of interaction has been undertaken in various countries including EU countries (Aslam & Corrado, 2012; Neira et al., 2018; Pittau et al., 2010), the United Kingdom (UK) (Ballas & Tranmer, 2012), the US (R. Fernandez & Kulik, 1981) and New Zealand (Aminzadeh et al., 2013); however to the best of my knowledge, this approach has never been applied to urban neighbourhoods in Australia.

The concept of social capital was defined in Chapter 2. It has been identified as one of the domain contributing to human wellbeing (Costanza et al., 2013) and empirical research

[44] Significant content in this section has been removed from the submitted manuscript to avoid redundancy of information already included elsewhere in the thesis.

across different countries has investigated its impact using various scales of observation: national (Helliwell & Putnam, 2004; Lawless & Lucas, 2010; Layard, 2005); regional (Ballas & Thanis, 2022; Rentfrow et al., 2009) and local (Aminzadeh et al., 2013; Vemuri et al., 2011). While human and social capital variables have often been considered in Australian LS research (Kubiszewski, Jarvis, et al., 2019; Shields et al., 2009), we are missing a systematic analysis of the impact of different dimensions of social capital (Helliwell & Putnam, 2004) on LS. This study seeks to address this gap, placing a particular focus on social capital influence at individual and neighbourhood levels.

Geographic clustering of LS scores has been reported in Europe (Jokela et al., 2015; Okulicz-Kozaryn, 2011; Rentfrow et al., 2015), the US (Rentfrow & Jokela, 2016) and Canada (Helliwell et al., 2019; Ziogas et al., 2023). Here I focus on geographic variations between neighbourhoods within an urban/ suburban context. For this purpose, I selected two metropolitan areas of Australia. One is on the East coast, the southeast Queensland area centred around Brisbane, the other on the West coast around Perth (Figure 4-3, Appendix C). Brisbane and Perth are both classified as "Beta" cities according to the Globalisation and World Cities Research Network (GaWC, 2020). These two regions are comparable in population and geographical spread and have growing demographic and economic significance. Larger metropolitan areas could have been chosen for this study, however, results from previous wellbeing research in Australia point to a different pattern of relationship between LS and LS predictors in Greater Perth compared to elsewhere across the country (Lignier et al., 2023)[45] and I sought to put this particular assumption to the test.

The large sample (nearly 4,000 respondents) used for this study mean that the findings have relevance beyond the two regions investigated here. They may be of interest when developing public policies that aim to enhance social cohesion and trust within local communities, specifically, public policies on urban social infrastructure.

The rest of this chapter is structured as follows: Section 4.2 briefly reviews the relevant literature; the methodology used for our project is described in Section 4.3, while results are presented in Section 4.4. Findings are discussed in Section 4.5, while in Section 4.6, I summarise the outcomes from this study and discuss their practical implications.

[45] This study is reported in Chapter 3 of this thesis.

4.2 Literature review

4.2.1 Geography of wellbeing

Geography of wellbeing refers to the study of spatial variations in the level of wellbeing and the factors that impact wellbeing (Weckroth et al., 2022). Findings from this body of research show that even after adjusting for differences in individual backgrounds and characteristics, significant differences exist between countries (Layard, 2005; Veenhoven, 2008), regions (Aslam & Corrado, 2012; Helliwell et al., 2019; Okulicz-Kozaryn, 2011; Pittau et al., 2010) or neighbourhoods (Ballas & Tranmer, 2012). There is some indication that geographical contexts affect LS more than momentary happiness (Schwanen & Wang, 2014).

Studies in the US and Canada report that people living in rural areas are happier than urban residents (R. Fernandez & Kulik, 1981; Helliwell et al., 2019), however evidence from Europe shows little difference in the level of quality of life between rural and urban areas in the richest countries of the European Union, while in the poorer countries of Eastern and Southern Europe, people residing in rural areas appear to have a lower perceived quality of life (Shucksmith et al., 2009). Others have emphasised that the degree of remoteness may be a better predictor of wellbeing than rurality: Gilbert et al. (2016) found that while residents living in remote rural areas in Scotland had a higher level of LS, there was no significant difference between accessible rural areas and urban areas.

Studies that investigated the variations in LS within urban areas found that variables such as accessibility, commuting time, safety, level of pollution and climate variables were contributing factors (Brereton et al., 2008; Ferrer-i-Carbonell & Gowdy, 2007; Stutzer & Frey, 2008; Weckroth et al., 2022). The influence of population density on LS is contested: some argue that overall district density has no significant impact (Ala-Mantila et al., 2018; Ferreira et al., 2013), others report that high density at census block level has a negative effect (Cramer et al., 2004; Helliwell et al., 2019; N. P. Li & Kanazawa, 2016). According to Ettema and Schekkerman (2016) and Ala-Mantila et al. (2018), subjective variables such as perceived quality of neighbourhood, perceived safety and subjective distance to amenities appear to be more significant predictors of wellbeing than objective characteristics.

The spatial attributes described above are often intertwined with socio-economic factors such as income inequality and unemployment level in the neighbourhood (Ala-Mantila et al., 2018). The relationship between income inequality and wellbeing is not clear. Higher inequality has been associated with lower reported levels of wellbeing in Europe

(Alesina et al., 2004) and in the US (Alesina et al., 2004; Oishi et al., 2011). However when using state level data, Glaeser et al. (2016) found that inequality had a small positive influence on happiness while Florida et al. (2013) noticed that it had no influence in metropolitan areas. It seems however that areas where there is a high inequality in LS have lower levels of average LS (Kubiszewski, Jarvis, et al., 2019; Ziogas et al., 2023). The influence of area level unemployment on individual wellbeing has also been examined: the consensus is that contextual unemployment has a positive influence on individual wellbeing as it acts as a social norm and softens the negative impact of individual unemployment (Clark, 2003; Clark & Oswald, 1994; Powdthavee, 2007).

4.2.2 The importance of social capital

The significance of local or regional social capital as a predictor of individual wellbeing has been confirmed by studies in Europe (Aslam & Corrado, 2012; Mouratidis, 2019; Neira et al., 2018; Weckroth et al., 2022), the US (Vemuri & Costanza, 2006; Vemuri et al., 2011) and New Zealand (Aminzadeh et al., 2013). Social capital is sometimes included in the analysis as a single proxy factor (Florida et al., 2013; Subramanian et al., 2000), however others integrate different dimensions of social capital as distinct variables: frequency of social contacts (Yuan, 2016), social trust (Subramanian et al., 2000) and community involvement (Gilbert et al., 2016). Trust in institutions is sometimes distinguished from trust in people and social networks from formal networks.

Social trust is the belief that those around you (neighbours, family etc.,) can be trusted and is considered a strong indicator of social capital at aggregate level (Helliwell & Putnam, 2004; Yuan, 2016). The positive relationship between institutional trust, freedom and happiness has been documented in many studies (Bruni, 2006; Frey & Stutzer, 2000; Veenhoven, 2000), while the national average level of interpersonal trust has been shown to have a positive effect on subjective wellbeing (Helliwell, 2003). When aggregated at the regional level, social trust and institutional trust were positively correlated with LS, but the influence of the aggregate regional mean variables was found to be stronger than the individual effect (Aslam & Corrado, 2012). Social networking is strongly associated with both higher levels of LS and higher levels of happiness (Aslam & Corrado, 2012; Neira et al., 2018), but not with eudemonic wellbeing (Gilbert et al., 2016).

Individual perceptions about the neighbourhood social and physical attributes have also been used as measures of social capital (Aminzadeh et al., 2013). A psychological sense of community, that is the perception that neighbours are helpful and could be relied upon if

necessary, the feeling that one belongs to the community was found to be associated with higher level of LS (Ma et al., 2018; Shields et al., 2009; Vemuri et al., 2011). Conversely, negative perceptions about the level of crime (Ambrey et al., 2014) and physical deterioration such as derelict buildings, litter and noise (Ettema & Schekkerman, 2016; Mouratidis, 2019) or pollution (MacKerron & Mourato, 2009) were reported as negative drivers of LS.

4.2.3 Multi-level analysis and heterogeneity

Multi-level analysis is a way to control for endogeneity caused by grouping (nested) behaviour of individuals. Multi-level analysis investigating geographic heterogeneity has been applied to a variety of topics including: self-rated health in US states (Subramanian et al., 2000); subjective wellbeing across census districts in the UK (Ballas & Tranmer, 2012); adolescent wellbeing in New Zealand neighbourhoods (Aminzadeh et al., 2013); subjective wellbeing across regions of Europe (Aslam & Corrado, 2012; Neira et al., 2018; Pittau et al., 2010) and in local neighbourhoods in Finland (Weckroth et al., 2022).

Multi-level Modelling (MLM) is the technique of statistical analysis that examines the influence of contextual factors on LS using the hierarchical structure of the data. MLM is particularly suitable for studying the role of contextual factors such as geography based cultural and socio-economic differences, in shaping up lifestyle behaviour (Ballas & Tranmer, 2012; de Leeuw & Meijer, 2008). MLM allows the group coefficients (intercepts and slopes) to be modelled and provides separate estimates of individual and contextual effects at different levels. (Pittau et al., 2010). MLM estimates variations both within and between the groups by allowing intercepts and slopes to vary simultaneously (Gelman & Hill, 2007).

The effects of contextual factors on the dependent variable have been described in various literatures as heterogeneity, however it is important to distinguish between two types of heterogeneity: *between-context* from *between-individual* heterogeneity (Duncan et al., 1998). Between-context heterogeneity is a higher-level form of heterogeneity that reflects differences *between* groupings or regions. On the other hand, between-individual refers to differences at a micro-level and reflects the different characteristics of the people *within* the grouping/region (Duncan et al., 1998; Neira et al., 2018).

4.3 Methodology

4.3.1 Data

This study uses data from Wave 18 (2018) of the HILDA survey. The descriptive summary of the database used for this study is as follows: 3,869 individual respondents nested[46] into 2,176 households nested into 390 statistical areas. A level 2 Statistical area (SA2) is adopted for this study: this means that the geographic size of a district may vary from a small neighbourhood in densely populated inner suburbs, to a relatively large area (several hundred km^2) in outer metropolitan districts (Australian Bureau of Statistics, 2016).

Table 4-1: Statistical profile of the study sample compared to reference populations

	Reference population [a]		**Sample**
	Greater Perth	**S E Queensland**	Total
N (population) n (sample)	2,305,394	3,565,856	3,869
n (Greater Perth Sample)			1,340
n (SE Queensland sample)			2,529
Area (km^2)	31,218	20,786	
Density (pop/ km^2)	74	172	
Median age	37.5	37.4	45.2
Median weekly household income ($)	1,833.3	1,790	2,571
People with University degree (%)	25.6	25.5	25.1
People born overseas (%)	39.6	31.6	23.1
People who speak LOTE at home (%)	22.5	18.4	7.1
Households who own home (%)	70.6	63.1	66.6
Low-income household (< $650/ week) (%)	16.0	14.9	10.9
High-income household (> $3000 / week) (%)	26.0	24.0	29.3

[a] Source 2021 census: https://www.abs.gov.au/census/find-census-data/quickstats/2021/5GPER

The comparative statistics between the reference populations and the study sample (Table 4-1) indicate that both metropolitan regions share similar key demographic and socio-economic characteristics except for the proportion of people born overseas and people speaking a Language Other than English (LOTE) that is greater in Greater Perth than in SE Queensland. Respondents in the study sample are older on average and households have a much higher median income compared to the reference populations. People born overseas, particularly people who speak a LOTE, are significantly under-represented. This selection bias could have implications for the generalisation of the study findings, especially the under-

[46] The relevance of the nested structure of the data to the Multi-level Modelling approach is discussed in the next section (4.3.2).

representation of immigrants, as empirical evidence suggests that ethnicity has a significant influence on subjective wellbeing (Bruna, 2021; Helliwell et al., 2019).

4.3.2 Statistical analysis

I adopt a three-level MLM for this analysis, with Level 1 representing the individual component, Level 2 the household component and Level 3 the SA2 component. Apart from modelling group coefficients, the use of MLM decomposes the total random variation into individual and group components. While group level predictors are themselves of interest, their inclusion may also reduce the unexplained group level variation which can be interpreted as a measure of the importance of the predictor (Pittau et al., 2010). The number of clusters should be large enough (>30) and the groups heterogeneous (Hox, 1998). MLM can be applied even where some groups have a size of 1 as long as there is a sufficient number of larger groups (Snijders & Berkhof, 2008). In this research, households with one observation were all retained, however all SA2 districts with less than 2 observations were discarded from the sample as groups with a single observation were problematic when estimating a model with random slope coefficients. The different metropolitan regions could arguably have been treated as an additional level of analysis. However, considering that there are only two clusters, I opted to treat regions as a fixed effect in the estimation.

4.3.3 Variables

The selection of variables (Table 4-6, Appendix A) reflects the three-level nested design: individual level variables, household level variables, statistical area level variables. Social capital variables are discussed separately.

4.3.3.1 Individual and household level variables

The selection of relevant individual socio-demographic variables was guided by the literature: age, gender, health, employment, marital status, education level. I also include variables specific to the Australian context such as indigenous status, speak a LOTE at home as a proxy for non-English speaking background (Ambrey & Fleming, 2014; Shields et al., 2009).

Household type was included as a potential predictor of LS (Ballas &Tranmer 2012), with ‘lone person household’ being the baseline and three identified types: ‘couple without children’ ‘couple with children’ and ‘single parent’. Household income is represented by ‘relative income’ based on the evidence that relative income matters more than absolute

income as predictor of LS (Clark et al., 2008). House ownership is also retained as a potential predictor (Ballas & Tranmer, 2012; Kubiszewski et al., 2018).

4.3.3.2 Statistical area (SA2) level variables:

Contextual variables representing SA2 socio-economic conditions were selected based on their potential relevance according to the literature. Income inequality is best represented by the Gini coefficient. In the absence of Gini coefficient data at SA2 level, two statistics were retained as a proxy for the measure of inequality: percentage of low-income households (with a weekly income <A$650) and percentage of high-income households (with a weekly income ≥ $A3,000). These variables can be assumed to represent respectively the bottom and the top of the Lorenz curve that determine the Gini coefficient (Florida & Mellander, 2016). I also include a contextual variable representing the area average unemployment level for 2018[47]. Rather than incorporating raw neighbourhood population density as an independent variable, I distinguish between urban and suburban neighbourhoods by using a dummy identifying neighbourhoods that are more sparsely populated (less than 100 people per km^2) (Neira et al., 2018). Previous studies have identified a small influence of neighbourhood ethnicity on individual LS (R. Fernandez & Kulik, 1981). Percentage of people speaking a LOTE at home (Kubiszewski, Zakariyya, et al., 2019) is identified as a proxy for ethnic diversity in the neighbourhood.

The contextual influence of the environment and the climate is also considered. To this purpose, I incorporate the following variables in the regression models: natural vegetation index (NDVI) representing "greenness" (Kubiszewski, Zakariyya, et al., 2019), average rainfall, and maximum temperature in summer (Florida et al., 2013).

4.3.3.3 Social capital variables

Following the methodology adopted in Aslam and Corrado (2012), Aminzadeh et al. (2013) and Neira et al. (2018), social capital was captured by the survey instrument at respondent level. District averages for each variable were then calculated using sample design weights.

Informed by the relevant literature discussed in Section 4.2, six dimensions of social capital are initially identified for this project: social trust, social connection, social engagement, psychological sense of community, neighbourhood perceived crime and safety,

[47] As this data was not available at SA2 level, I use the data for SA4 level instead.

neighbourhood perceived shabbiness. Psychological sense of community reflects the individual's perception about the neighbourhood social cohesion and social harmony. The construct was first introduced by Vemuri et al. (2011) who labelled it social capital index. A similar variable was used by Aminzadeh et al. (2013) who combined it with neighbourhood perceived safety into an overall 'social cohesion' construct. The details for each social capital construct are shown in Table 4-2 and underlying survey questions can be found in Table 4-7. Cronbach Alpha calculations reveal a high level of internal consistency for each construct. Institutional trust was not believed to be relevant here as the neighbourhoods investigated are subject to remarkably similar political and governance structures.

Table 4-2: Initial social capital constructs

Construct	**Number of underpinning items**	**Cronbach alpha**
Social trust	1	N/A
Social connection	6	0.623
Social engagement	7	0.744
Psychological sense of community	5	0.878
Neighbourhood perceived crime & safety	4	0.869
Neighbourhood perceived shabbiness	4	0.688

Pairwise correlations between the different constructs were estimated. A high level of correlation was found between social connection and social engagement at both individual (0.51) and district level (0.75). To avoid multicollinearity issues, the two constructs were merged into an 'engagement and connection' composite variable. Similarly, neighbourhood perceived safety and neighbourhood perceived shabbiness with correlations at 0.60 and 0.70, were merged into 'neighbourhood safety issues & shabbiness'.[48]

4.3.4 Unexplained group level heterogeneity

Some of the group level random effects identified by the analysis could be correlated with the regressors, for instance heterogeneity in social capital variables between SA2 could be correlated with the corresponding individual regressors. While using a MLM model, this heterogeneity can be resolved by including the group means for these variables in the

[48] Merging by straight averaging was possible as underlying ordinal variables were measured on the same scale: 1 to 6 for both social connection and social engagement; 1 to 5 for perceived crime and safety and perceived shabbiness.

regression (Mundlak, 1978). To avoid problematic multicollinearity between the individual level variables and the group mean variables, I use a mean-centred level 1 covariate as an instrumental variable (Snijders & Berkhof, 2008), this makes it possible to assess the relative position of the individual as well as the effect of the absolute group factors.

When calculating the district mean for social capital variables, design weights reflecting the different probability of selection for different individuals, are used to correct for sampling bias (Aslam & Corrado, 2012). As the HILDA weight represents the probability of an individual being selected by reference to the entire population (Watson, 2012), a corrected weight is calculated by reference to the statistical district to reflect the probability of being selected within the district. The aggregate mean social capital variable $\overline{(C_k)}$ is determined as follows:

$$\overline{C_k} = \frac{1}{k_D} \times \sum_{i=1}^{k_D} w_{di} \times C_{ijk}$$

where w_{di} is respondent *i* weight in the district, k_D is the number of respondents in the district and C_{ijk} is the social capital variable measure of respondent *i*.

4.3.5 Estimated regression models

Six successive models are estimated. Model 0 is an empty model of individuals nested within households nested within SA2 areas with no independent variables:

$$y_{ijk} = \beta_{000} + v_{00k} + u_{0jk} + e_{ijk} \ (0)$$

where β_{000} is the overall LS mean, v_{00k} is the intercept adjustment for each SA 2 area, u_{ojk} is the intercept adjustment for each household and e_{ijk} is an individual error term. $i = 1 \ldots I$ represents individual respondents, $j = 1 \ldots . J$ represents households, and $k = 1 \ldots . K$ represents SA2 areas.

Model 1 extends Equation (0) by including individual level socio-demographic variables:

$$y_{ijk} = \beta_{000} + \gamma_{100} X_{ijk} + v_{0k} + u_{0jk} + e_{ijk} \quad (1)$$

where X_{ijk} is a vector of individual socio-demographic variables.

Model 2 extends Equation (1) by including household level variables:

$$y_{ijk} = \beta_{000} + \gamma_{100} X_{ijk} + \gamma_{010} Z_{jk} + v_{0k} + u_{0jk} + e_{ijk} \ (2)$$

where Z_{kj} is a vector of household level variables.

Model 3 extends Equation (2) by including mean-centred individual social capital variables as well as the aggregate value of the social capital variables at SA2 level, and contextual socio-economic and environmental variables.

$$y_{ijk} = \beta_{000} + \gamma_{100}X_{ijk} + \gamma_{010}\,Z_{jk} + \delta_{100}(C_{ijk} - \overline{C_k}) + \delta_{001}\overline{C_k} + \theta_{001}D_k + v_{0k} + u_{0jk} + e_{ijk} \quad (3)$$

where C_{ijk} is a vector of social capital variables at individual level, $\overline{C_k}$ is the aggregate mean of a social variable for area k and D_k is a vector of contextual variables for area k.

Model 4 extends Equation (3) and accounts for between-group heterogeneity by making the coefficients of the individual social variables dependent on the SA2 area. Snijders and Bosker (2011, p. chapter 5)) recommend using the primary variable rather than the mean-centred variable as the control individual level variable.

$$y_{ijk} = \beta_{000} + \gamma_{100}X_{ijk} + \gamma_{010}\,Z_{jk} + \delta_{100}C_{ijk} + \delta_{001}\overline{C_k} + \theta_{001}D_k + v_{0k} + v_{1k}C_{ijk} + u_{0jk} + e_{ijk} \quad (4)$$

where v_{1k} is the slope adjustment term for the social capital variable 1 in area k.

Model 5 modifies Equation (4) and instead of using random slope coefficients for C_{ijk}, introduces cross-interaction terms between the individual social capital variables and their mean at SA2 level.[49] This interaction term for social capital variables is $\delta_{101}C_{ijk}\overline{C_k}$. It means that the slope of the individual social capital variables effectively vary depending on the SA2 as it does for Model 4; however instead of producing one coefficient estimate per area as in Model 4, it produces two unique estimates: δ_{100} and δ_{001} (Neira et al., 2018).

$$y_{ijk} = \beta_{000} + \gamma_{100}X_{ijk} + \gamma_{010}\,Z_{jk} + \delta_{100}C_{ijk} + \delta_{001}\overline{C_k} + \delta_{101}C_{ijk}\overline{C_k} + \theta_{001}D_k + \theta_{101}X_{ijk}D_k + v_{0k} + u_{0jk} + e_{ijk} \quad (5)$$

To minimise the possibility of heteroskedasticity, models were estimated using robustness checks such as robust variances and independent residuals (Pek et al., 2018). I checked for normality of residuals using visual tests including kernel density and standardised P-P plot (Figures 4-1 & 4-2); given the large sample limitation of the Shapiro-Wilk test (Royston, 1982).

[49] Interaction terms are also included for ethnicity and unemployment.

4.4 Results

4.4.1 Descriptive statistics

Descriptive statistics are summarised in Table 4-3. The average LS in the study sample is 7.94 on a 0-10 scale which is very close to the 7.91 Australian within-person average for the period 2000-17 reported by Kubiszewski et al. (2020). Figure 4-4 (Appendix C) provides some visual evidence of the geographical clustering of LS scores in both metropolitan regions. Comparison of social capital average scores with results from prior research is often meaningless because of differences in scales and methodologies. Variations of aggregate scores between neighbourhoods remain high with a standard deviation well over 50 % of the variation at individual level. Figures 4-5 to 4-8 visually illustrate the diversity in social capital variables scores across neighbourhoods in both metropolitan areas.

Table 4-3: Summary descriptive statistics for selected variables

Variables	n	Mean	Std. dev.	Min	Max
Life satisfaction (0-10) (Dependent V.)	3,868	7.942	1.428	0	10
Individual variables					
age	3,869	45.23	18.94	15	99
female (0/1)	3,869	0.53	0.50	0	1
indigenous (0/1)	3,869	0.03	0.17	0	1
speak LOTE (/1)	3,869	0.07	0.26	0	1
higher education (0/1)	3,869	0.25	0.43	0	1
self -assessed health (1-5)	3,567	3.33	0.95	1	5
unemployed (0/1	3,869	0.04	0.20	0	1
Household variables					
couple no children (0/1)	3,868	0.31	0.46	0	1
couple with children (0/1)	3,869	0.28	0.45	0	1
single parent (0/1)	3,869	0.10	0.31	0	1
household inc. (A$ '000 per year)	3,869	134	137	0	2,608
household relative inc.	3,869	1.41	1.40	0	36.23
own home (0/1)	3,869	0.67	0.47	0	1
Social capital variables (individual)					
social trust	3,586	4.63	1.69	1	7
engagement & conn.	3,575	3.07	0.81	0.83	6.5
psych sense of community	3,605	3.96	1.08	0.75	7
neighb. safety issues & shabbiness	3,595	2.52	0.70	1	5
District social capital variables (aggregate mean)					
sa2_ social trust	3,869	4.56	0.82	0.89	6.70
sa2_ connection & engagement	3,869	3.07	0.48	0.78	5.66
sa2_ psych. sense of community	3,869	3.96	0.65	0.88	6.38
sa2_safety issues & shabbiness	3,869	2.50	0.43	0.48	4.22
Sa2 contextual variables					
sa2_ sparsely populated (0/1)	3,869	0.10	0.30	0	1
sa2_prop speak LOTE (%)	3,869	17.5	10.8	4	66.1
sa2_prop, low income (%)	3,869	15.6	5.4	4	35.3
sa2_proportion high income (%)	3,869	24.7	10.5	5	56.9
sa2_proportion higher ed (%)	3,869	23.7	12.0	5.1	55.4
sa2_prop. unemployed (%)	3,869	5.9	1.3	4	9.3
sa2_natural vegetation index	3,869	0.304	0.102	0.043	0.562
sa2_annual rainfall (mm)	3,869	953.7	285.8	591.3	1613.9
sa2_maximum temp in Summer (°C)	3,869	30.3	1.1	26.2	33.5

4.4.2 Model 0 (empty model)

Results for Model 0 (null hypothesis) are shown in Table 4-4. Random intercept effects are significant at all levels. The intraclass correlation coefficient (ICC) measures the correlation between observations within a particular class. It is calculated as the ratio of the between-cluster variance and the sum of between and within-cluster variances (Raudenbush & Sampson, 1999). The ICC at SA2 level is small compared to the ICC at household level revealing an important variance between household clusters.

Table 4-4: Intercept and random effect parameters for the null hypothesis model

Observations (n)	3,869		
Intercept β_{000}	7.819		
Random effect:	Estimate	Std dev.	ICC
Level:			
SA2 v_{00k}	0.109***	0.027	0.053
Household u_{0jk}	0.546***	0.055	0.318
Respondents e_{ijk}	1.406***	0.049	

Significant at *** p< 0.01 level **p< 0.05 level * p< 0.1 level

4.4.3 Model 1 and Model 2

Model 1 incorporates level 1 socio-demographic variables while household variables are added in Model 2. Results for both models are shown in Table 4-5. The significant drop in the SA2 random intercept variance (from 0.109 for Model 0 to 0.051 for Model 2) shows that a substantial portion of the initial between-group heterogeneity in LS between SA2 is explained by socio-demographic variables.

Being healthy is by far the most important positive contributor of LS. Age (in quadratic form) is another significant contributor; being female is a positive factor; being unemployed is associated with lower LS, as is having a higher education. Among household type variables, living as a couple either with or without children has a positive effect on LS compared to living in a single person household. Relative income measured as the ratio between household income and median income in the statistical area is a positive contributor as is house ownership. Finally, the fixed effect dummy variable for the Greater Perth region is highly significant suggesting a different pattern of relationship for that region.

Table 4-5: Summary statistics for Model 1 and Model 2

	Model 1		Model 2	
Observations (n)	3,566		3,566	
	Coeff	Std err	Coeff	Std err
Intercept	6.421	0.164	6.294	0.170
Individual variables:				
age	-0.040***	0.006	-0.048***	0.006
age square	0.001***	0.000	0.001***	0.000
female	0.129***	0.040	0.148***	0.040
indigenous	0.086	0.166	0.138	0.165
speak LOTE	-0.101	0.089	-0.102	0.088
higher education	-0.059	0.044	-0.112***	0.044
self-assessed health	0.601***	0.027	0.584***	0.027
unemployed	-0.325***	0.125	-0.276**	0.123
Household variables:				
couple no children			0.227***	0.059
couple with children			0.297***	0.058
single parent			-0.054	0.085
relative household income			0.059***	0.021
own house			0.193***	0.057
greater Perth (dummy)	-0.169***	0.059	-0.184***	0.057
Random effect -intercept:				
SA2 level	0.065***	0.018	0.051***	0.017
household level	0.313***	0.056	0.299***	0.055
individual level	1.228***	0.068	1.217***	0.066
Akaike Information Criteria	11712.61		11649.71	

Significant at *** p< 0.01 level, **p< 0.05 level, * p< 0.1 level

4.4.4 Models 3, 4 and 5

These models introduce social capital variables at individual and SA2 levels as well as contextual variables at SA2 level. Summary statistics for each model are shown in Table 4-6. Model 3 allows for random intercepts, i.e., it captures between-context heterogeneity. Model 4 allows for random slope coefficients for the social variables. This captures between-individual heterogeneity through group dependence (Snijders & Bosker, 2011). Model 5 includes interactions terms for the social capital variables without random slopes. This may provide explanations for the geographical variability of the individual social capital coefficients (Schynz, 2002). I also include interactions terms for ethnicity and unemployment.

The introduction of social capital variables causes a further drop in the random intercept variance at SA2 level from 0.051 (Model 2) to 0.036 (Model 3). Random effects of intercept at SA2 level remain significant for Models 3 and 5. Coefficients for most individual and household level factors remain stable across Models 3, 4 and 5 with minor variation from Model 2. However, the coefficients for 'speaking LOTE' and 'being unemployed' lose their significance in Model 5 when an interaction term with the area level variable is introduced.

Results for Model 3 show that individual social trust, 'engagement and connection' and 'psychological sense of community' are significant positive contributors of LS. Conversely, 'perception about safety issues and shabbiness' has a significantly negative relationship with LS. Area level aggregate for social trust and 'social engagement and connection' are also positively associated with individual LS, but aggregate 'psychological sense of community' has no significant influence. The aggregate mean 'neighbourhood safety issues and shabbiness' has a significant negative coefficient. Coefficients for aggregate social capital means tend to be larger than coefficients for corresponding variables at individual level.

In Model 4, slope coefficients for individual social capital variables vary across SA2. The only coefficient for which the variation is significant is 'neighbourhood safety issues and shabbiness'. The average coefficients for individual social capital variables are remarkably similar to those obtained for Model 3. Coefficients for SA2 aggregate are much smaller than in Model 3 and become non-significant. This outcome, similar to the results in Neira et al. (2018) suggests that the heterogeneity in the effect of social capital variables between SA2 is likely to be attributable to between-individual heterogeneity rather than between-group heterogeneity (Duncan et al., 1998).

Model 5 introduces cross-level social capital interaction terms and explores the possible causes for between-individual heterogeneity (Duncan et al., 1998). The results suggest that 'engagement and connection' is the only social capital variable, for which the contextual term and the individual term have a combined effect on LS. In other words, the impact of *individual* social engagement and connection on individual LS is influenced by the *overall* level of social engagement and connection in the area. Both the individual and mean variables have higher coefficients than in the previous models, however the interaction term coefficient is significantly negative.

None of the other contextual socio-economic variables appear to have a significant influence on LS. The introduction of an interaction term between the individual variable and the contextual variable for ‘speak LOTE’ and unemployment in Model 5 does not fundamentally alter this pattern. The interaction term for ‘speak LOTE’ has a weakly significant negative effect. Likewise, the environmental contextual variables representing green vegetation and climate are not found to significantly impact LS. The fixed effect identifier for Greater Perth is weakly significant in Model 3 and 5 and below significance level in Model 4.

Table 4-6: Summary statistics for Models 3, 4 and 5

	Model 3		Model 4		Model 5	
Observations (n)	3,478		3,470		3,470	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Intercept	5.849	0.970	5.813	0.959	4.720	1.296
Individual variables:						
age	-0.045***	0.006	-0.045***	0.006	-0.045***	0.006
age square	0.001***	0.000	0.001***	0.000	0.001***	0.000
female	0.088**	0.039	0.088**	0.039	0.086***	0.039
indigenous	0.197	0.169	0.189	0.167	0.185	0.168
speak LOTE	-0.138	0.087	-0.143*	0.086	0.154	0.180
higher education	-0.182***	0.047	-0.178***	0.047	-0.179***	0.047
self-assessed health	0.514***	0.026	0.513***	0.026	0.513***	0.026
unemployed	-0.307**	0.120	-0.313***	0.120	-0.585	0.613
Household variables:						
couple no children	0.206***	0.054	0.204***	0.054	0.212***	0.054
couple with children	0.247***	0.058	0.252***	0.058	0.256***	0.058
single parent	-0.050	0.083	-0.040	0.085	-0.037	0.084
relative household income	0.041*	0.024	0.042*	0.024	0.042*	0.023
own house	0.114**	0.056	0.114**	0.056	0.114**	0.056
Social capital: individual [a]:						
social trust	0.055***	0.014	0.055***	0.014	0.063	0.079
engagement & connection	0.192***	0.034	0.192***	0.033	0.605***	0.157
psych. sense of community	0.069***	0.023	0.069***	0.023	-0.036	0.129
safety issues & shabbiness	-0.161***	0.038	-0.163***	0.038	-0.113	0.198
SA2 social capital aggregate:						
social trust	0.074**	0.035	0.023	0.035	0.023	0.093
engagement & connection	0.264***	0.065	0.065	0.069	0.490***	0.187
psych. sense of community	0.088	0.054	0.020	0.054	-0.078	0.146
safety issues & shabbiness	-0.192**	0.076	-0.033	0.076	0.021	0.221
SA2 contextual variables:						
sparsely populated	0.119	0.103	0.092	0.102	0.123	0.102
prop low income	-0.001	0.008	-0.001	0.008	-0.001	0.008
prop high income	-0.003	0.004	-0.003	0.004	-0.003	0.004
prop speak LOTE	-0.001	0.003	-0.002	0.003	0.001	0.003
prop unemployed	-0.007	0.026	-0.005	0.026	-0.006	0.026
natural vegetation index (sa2)	-0.035	0.405	0.040	0.406	-0.017	0.411
Annual rainfall (sa2)	0.000	0.000	0.000	0.000	0.000	0.000
Max temp in summer (sa2)	-0.002	0.030	-0.001	0.030	0.000	0.030
Greater Perth (D)	-0.128*	0.077	-0.113	0.077	-0.128*	0.077

[a] mean centred variable in Model 3, full variable in Model 4 and Model 5' Significant at *** p< 0.01 level, **p< 0.05 level, * p< 0.1 level.

Table 4-6 (ctd.)

	Model 3		Model 4		Model 5	
	Coeff	Std. err.	Coeff		Coeff	Std. err.
Interaction terms indiv × SA2						
social trust					-0.002	0.017
engagement & connection					-0.132***	0.049
psych. sense of community					0.026	0.032
safety issues & shabbiness					-0.020	0.078
speak LOTE					-0.013*	0.007
unemployed					0.046	0.102
Random effect_ intercept:						
SA2 level	0.036**	0.016	0.000	0.000	0.038**	0.016
household level	0.253***	0.052	0.245	0.051***	0.250***	0.052
Individual level	1.169***	0.065	1.164	0.064***	1.167***	0.065
Random effect_ slope:						
social trust			0.000	0.000		
engagement & connection			0.000	0.000		
psych. sense of community			0.000	0.000		
safety issues & shabbiness			0.008	0.003***		
Akaike Information Criteria	11172.03		11150.17		11149.82	

[a] mean centred variable in Model 3, full variable in Model 4 and Model 5' Significant at *** p< 0.01 level, **p< 0.05 level, * p< 0.1 level.

4.5 Discussion

The small unexplained random effect at SA2 level in Model 3 suggests that socio-demographic variables and social capital variables explain much of the variations in LS between SA2. It is much larger than the random effect at group level in the Aslam and Corrado (2012) and Neira et al. (2018) studies where the clusters were large regions in the EU, but it is comparable to the variance at neighbourhood level in Aminzadeh et al. (2013) regression models.[50] The unexplained random effect at household level remains relatively large as in Ballas & Tranmer (2012) indicating the presence of idiosyncratic differences between households.

The importance of factors representing social capital at individual level is confirmed by this research. Specifically, social trust (Helliwell & Putnam, 2004; Neira et al., 2018; Subramanian et al., 2000) and 'engagement and connection' (Aminzadeh et al., 2013; Gilbert et al., 2016; Yuan, 2016) are significantly positive contributors of LS. The variable

[50] Aminzadeh et al (2013) measured wellbeing on a 0 to 5 scale, so the absolute value of the variance of the intercept is predictably lower than for that study.

'psychological sense of community' that reflects individual perception about the level of social connection and harmony within the neighbourhood also has a positive impact on LS. The same outcome was reached by Aminzadeh et al. (2013) (social cohesion) in their study of adolescent wellbeing in New Zealand. Conversely, Vemuri et al. (2011)' social capital index based on the same dimensions was not found to be a significant driver of LS in metropolitan Baltimore.

Individual perception of safety issues and shabbiness in the neighbourhood has a significant negative impact on LS reflecting existing evidence (Ettema & Schekkerman, 2016; Mouratidis, 2019). This outcome might be surprising as the actual rate of violent crime[51] in both metropolitan areas is around 1,200 per 100,000 which is close to the Australian average (Australian Bureau of Statistics, 2023b), but much lower than for Philadelphia, a comparable Beta ranked city in the US.[52] This result is consistent with previous evidence that incidence of crime has little relationship with people's perception of crime (Veenhoven, 2002) and that perceived crime levels are a more significant negative contributor to LS than actual crime levels (Ambrey et al., 2014; Larson, 2010).

This study finds little evidence of contextual influence for social capital factors on LS: the results from the random slope coefficients model suggest that differences between SA2 are generally attributable to compositional effects rather than contextual effects. The exception is 'social engagement and connection" where the aggregate variable has a strong positive coefficient when an interaction term with the individual level variable is included. This suggests that the neighbourhood level of social connection and engagement interacts with the corresponding variable at individual level. The negative interaction factor can be interpreted as meaning that where aggregate social engagement and connection is high, the influence of individual level engagement and connection will be reduced. Only very few studies have considered the influence of area level social connection and engagement on individual LS. Aminzadeh et al (2013) found a positive influence for membership in community organisations, Neira et al (2018) reported a positive association for informal and formal networks, but no significant influence for civic engagement, a result also reached by

[51] Rate of violent crime included the following prosecuted offenses: homicide, assault including sexual assault, robbery, theft, abduction, and unlawful entry with intent.

[52] Rate of violent crime for Philadelphia in 2018 was 8,043 per 100,000: US Federal Board of Investigation, 2018 Crime in the United States : https://ucr.fbi.gov/crime-in-the-u.s/2018/crime-in-the-u.s.-2018/tables/table-8/table-8-state-cuts/pennsylvania.xls

Aslam and Corrado (2012). When interpreting these results, it is important to bear in mind that the two latter studies examined large regions (NUTS1-3) in different countries in Europe rather than urban neighbourhoods.

The influence of urbanity/ rurality was measured through the 'sparsely populated' dummy. It appears that this variable was not a significant contributor confirming earlier outcomes that a 'rural' residence has no significant influence on wellbeing when the area is accessible (Gilbert et al., 2016; Weckroth et al., 2022). Neither of the two proxy variables for income equality are significant. This outcome aligns with some earlier results (Florida et al., 2013; Weckroth et al., 2022), but challenges others, for instance Ala-Mantila et al. (2018) found that people had a higher quality of life where the proportion of high income earners was higher.

Individual ethnicity has often been identified as a determinant of LS, but very few studies have considered the influence of neighbourhood ethnicity. The consensus is that being of a non-English background (Kubiszewski et al., 2018) or belonging to an ethnic minority (Aminzadeh et al., 2013; Oswald & Wu, 2011) is associated with lower LS levels. A recent Canadian study also found that neighbourhoods with a high proportion of foreign born had lower average LS (Ziogas et al., 2023). The analysis of our data shows no significant influence for ethnicity on LS at either individual or neighbourhood level. However, the negative coefficient for the interaction term suggests that being a person of non-English speaking background living in a neighbourhood with a high percentage of non-English speakers may have a negative impact on LS. This result needs to be interpreted with caution considering that non-English speakers were under-represented in our sample.

This study confirms earlier findings that being unemployed tends to be associated with lower levels of LS. There is also strong empirical support in the literature for the argument that contextual unemployment might mitigate the effect of individual unemployment by acting as a social norm (Ballas & Tranmer, 2012; Clark, 2003; Powdthavee, 2007). This finding about contextual unemployment is not replicated in this study even when an interaction term is included. This might be explained by the relatively low level of contextual unemployment in the study area (5.9%) at the time of survey. By comparison the unemployment rate in South Africa for the Powdthavee study was around 13% (Powdthavee, 2007) and it was 8.6% in the UK in 1991 (World Bank, 2023b) when the data used by Ballas & Tranmer was collected.

Vegetation index was found to be a statistically significant LS factor in previous research (Kubiszewski, Zakariyya, et al., 2019); similarly, temperature and to a lesser extent rainfall, have been found to influence average LS (Brereton et al., 2008; Florida et al., 2013; Lignier et al., 2023). Neither of these environmental variables significantly impact LS in this sample. While previous research that examined the influence of climate and the environment on LS covered regions with different climates, the present study covered areas where climate variations are small. A similar conclusion to mine was reached from data collected in the urban area of Baltimore (US) (Vemuri et al., 2011).

Individual socio-economic variables mostly behave as expected from similar research in Australia. Age is a consistent predictor with a U shape non-linear relationship (Frijters & Beatton, 2012); being female is associated with higher levels of LS. Evidence about the influence of sex on LS is mixed, with some studies predicting a positive association for female (Kubiszewski, Jarvis, et al., 2019; Neira et al., 2018) others a negative association (Aminzadeh et al., 2013; Ballas & Tranmer, 2012). The negative association between having a university degree and LS that was noted in some studies is confirmed here (Ambrey & Fleming, 2014).

According to my results, household structure matters: couples with or without children seem to have higher LS levels compared to single person households. This differs somewhat from earlier MLM studies in the UK where couples without children had higher levels of LS but couples with children had lower levels (Ballas & Tranmer, 2012).[53] House ownership is consistently a significant positive predictor of LS. This aligns with earlier results from the UK (Ballas & Tranmer, 2012) and Australia (Kubiszewski et al., 2018), but a US study found that home ownership was a negative predictor of metropolitan wellbeing (Florida et al., 2013). Relative household income is a significant positive contributor of LS in all models reflecting predictive models by Clark et al. (2008). Household income was also found to be a positive contributor in many LS/ social capital studies (Aslam & Corrado, 2012; Neira et al., 2018; Rentfrow et al., 2009).

A secondary objective of this study was to test whether the seemingly different pattern of relationship between LS and LS determinants in the Greater Perth region was confirmed. The two regions were identified through the inclusion of a fixed effect dummy

[53] Some Australian studies also reported that the number of children in the household was negatively associated with LS (Ambrey & Fleming, 2014; Kubiszewski et al., 2018).

variable. The significantly negative coefficient for the Greater Perth dummy in Models 1 and 2 seem to support previous findings that *ceteris paribus* a certain configuration of LS determinants would result in lower predicted LS in that region (Lignier et al., 2023). The coefficient remains negative when social capital and contextual variables are introduced but with a much weaker level of significance. This might suggest that the positive effect of social capital variables on LS in Greater Perth somewhat mitigates the differences with other regions.

4.6 Conclusion

The primary objective of this study was to analyse the influence of individual and contextual social capital variables on LS within a metropolitan context in Australia using MLM. This study is the first one, to the best of my knowledge, which uses MLM with three levels of aggregation to investigate LS and social capital in metropolitan regions within a single country.

I find that only a moderate proportion of the unexplained variation in LS prediction was attributable to differences between spatial clusters, while the difference between households is much more significant. These results reflect similar findings from MLM studies at neighbourhood scale conducted in the UK and in New Zealand. I also find that most of the spatial heterogeneity is attributable to compositional effects (i.e., distinct characteristics of respondents living in different area) rather than contextual effects (variations linked to the specific social capital characteristic of the area).

My results corroborate previous findings that factors such as social trust, social engagement connection, and psychological sense of community representing individual contribution to social capital are strong positive contributors of individual LS. Negative individual perceptions about the neighbourhood such as safety issues and physical deterioration seem to have a deeper (negative) impact on LS, than positive perceptions about the neighbourhood social attributes. The influence of contextual social capital on individual LS appears to be limited to the interaction between individual and aggregate levels of social connection and engagement. Overall, our findings are consistent with the hypothesis that social capital will shape individual wellbeing (Coleman, 1988; OECD, 2001); however they do not support previous findings of a significant influence for contextual socio-economic variables such as income inequality, contextual unemployment and neighbourhood ethnicity.

I acknowledge several limitations for this research. Firstly, as noted in the methodology section, the study sample is somewhat biased towards older people with higher income, and households from non-English speaking background are under-represented. This may explain the non-significance of some contextual variables such as income inequality, unemployment, and ethnicity. Secondly, the number of respondents in some of the SA2 is very small, consequently idiosyncratic individual data may have a disproportionate effect on the area means (Helliwell et al., 2019). Thirdly, I do not account for possible spillover effects where average level of LS and social capital for an area could be influenced by neighbouring areas (Ziogas et al., 2023). Finally, as noted by Neira et al (2018), the lack of consistency in the definition of social capital dimensions and the absence of independently measured aggregate social capital indicators make inter-research comparisons hazardous.

Notwithstanding the above caveats, this research contributes to the pool of knowledge about the impact of social capital on individual wellbeing. The methodology used here can be replicated to other metropolitan areas anywhere in the world and applied to other wellbeing indicators such as happiness or mental health. My findings will inform government social policy in urban areas, for instance the building of urban infrastructure that promote social access and encourage social activities such walking paths, community playgrounds, and the remedying of physical urban deterioration and crime to reinforce the perception of personal safety. As argued by Wilkinson and Pickett (2009), the positive impact of community engagement and connection, and individual psychological sense of community on SWB suggest that access to urban and social infrastructure needs to be accompanied with better inclusion of all groups within the community to achieve better social outcomes.

4.7 Appendix to Chapter 4

4.7.1 Variables used for this project

Table 4-7: List of variables used for this project

Name	Description	Type	Level	Source
Dependent variable				
life_sat	Individual life satisfaction	Continuous (0-10)	DV	Wave 18[1]
Socio-demographic variables				
age	age of respondent	continuous	level 1	Wave 18
agesq	age square	continuous	level 1	Wave 18
female2	gender female	dummy	level 1	Wave 18
atsi2	indigenous status	dummy	level 1	Wave 18
lote2	speak LOTE	dummy	level 1	Wave 18
edhigh2	has a university education	dummy	level 1	Wave 18
rgh2	self-assessed health	ordinal	level 1	Wave 18
unemployed2	unemployed looking for work	dummy	level 1	Wave 18
individual social capital variables				
trust	social trust	continuous	level 1	Wave 18
socoh	social engagement and connection	continuous	level 1	Wave 18
nghatt	psychological sense of community	continuous	level 1	Wave 18
nghdef	neighb. safety issues & shabbiness	continuous	level 1	Wave 18
Household variables				
couplenc	couple no children	dummy	level 2	Wave 18
couplewc	couple with children	dummy	level 2	Wave 18
singlepar	single parents	dummy	level 2	Wave 18
hh_relinc	relative income/ median area income	continuous	level 2	Wave 18
house_own2	own house or mortgage	dummy	level 2	Wave 18
Area contextual variables				
sa2_sparse	Sparsely populated sa2 (< 100/ km^2)	dummy	level 3	Census [2]
sa2_lote	% speak LOTE at home in sa2	continuous	level 3	Census
sa2_lowinc	% low income households in sa2	continuous	level 3	Census
sa2_highinc	% high income households in sa2	continuous	level 3	Census
sa2_unempl	Area unemployment rate	continuous	level 3	[4]
sa2_ndvi	normalised diff vegetat. index (0-1)	continuous	level 3	B.O.M.[3]
sa2_rainfall	average annual rainfall	continuous	level 3	B.O.M.
sa2_tempmax	max temperature hottest month	continuous	level 3	B.O.M.
area mean social capital				
sa2_trust	social trust	continuous	level 3	Wave 18
sa2_socoh	social engagement and connection	continuous	level 3	Wave 18
sa2_nghatt	psychological sense of community	continuous	level 3	Wave 18
sa2_nghdef	neighb. safety issues & shabbiness	continuous	level 3	Wave 18

[1] HILDA Survey Wave 18 (2018): https://melbourneinstitute.unimelb.edu.au/hilda

[2] Census data:2021 Census QuickStats: https://www.abs.gov.au/census/find-census-data/quickstats/2021/5GPER

[3] Bureau of Meteorology (B.O.M.) average observations: 2000-2020: http://www.bom.gov.au/climate/data-services/

[4] Australian Government: Labour Market Insights: https://labourmarketinsights.gov.au/regions/all-regions-abs-sa4/ Statistics are for ABS Statistical Area Level 4 (SA4)

Table 4-8: Survey questions relating to social capital constructs

Social capital variable	HILDA Survey questions (summarized)	Measurement
Social trust (1)	most people would try to take advantage of you if they got a chance	(1-7) agreement
Social connection (6)	chat with your neighbours	(1-6) Never- very often
	telephone, mail email contact with friends & family	(1-6) Never- very often
	make time to attend service at place of worship	(1-6) Never- very often
	talk about current affairs with friends & family	(1-6) Never- very often
	make time to keep in touch with friends	(1-6) Never- very often
	see members of my extended family	(1-6) Never- very often
Social engagement (7)	attend event that bring people together	(1-6) Never- very often
	get involved in activities for a union, politics	(1-6) Never- very often
	encourage others to get involved in a group	(1-6) Never- very often
	volunteer your time to get involved in boards or similar	(1-6) Never- very often
	get in touch with local politician or councillor	(1-6) Never- very often
	give money to charity if asked	(1-6) Never- very often
	active member of a sporting/ hobby community club	Yes/ No
Psychological sense of community (5)	neighbours help each other out	(1-5) Never- very comm
	neighbours do things together	(1-5) Never- very comm
	this is a close-knit community	(1-7) agreement
	people in this neighbourhood can be trusted	(1-7) agreement
	people around here are willing help their neighbours	(1-7) agreement
Neighbourhood perceived crime & safety (4)	neighbourhood: teenagers hanging around on the streets	(1-5) Never- very comm
	neighbourhood: people being hostile and aggressive	(1-5) Never- very comm
	neighbourhood: vandalism and damage to property	(1-5) Never- very comm
	neighbourhood: burglary and theft	(1-5) Never- very comm
Neighbourhood perceived shabbiness (4)	neighbourhood: traffic noise	(1-5) Never- very comm
	neighbourhood: noise from airplanes, trains industry	(1-5) Never- very comm
	neighbourhood: homes and gardens in bad condition	(1-5) Never- very comm
	neighbourhood: rubbish and litter lying around	(1-5) Never- very comm

4.7.2 Normality of residuals: visual tests

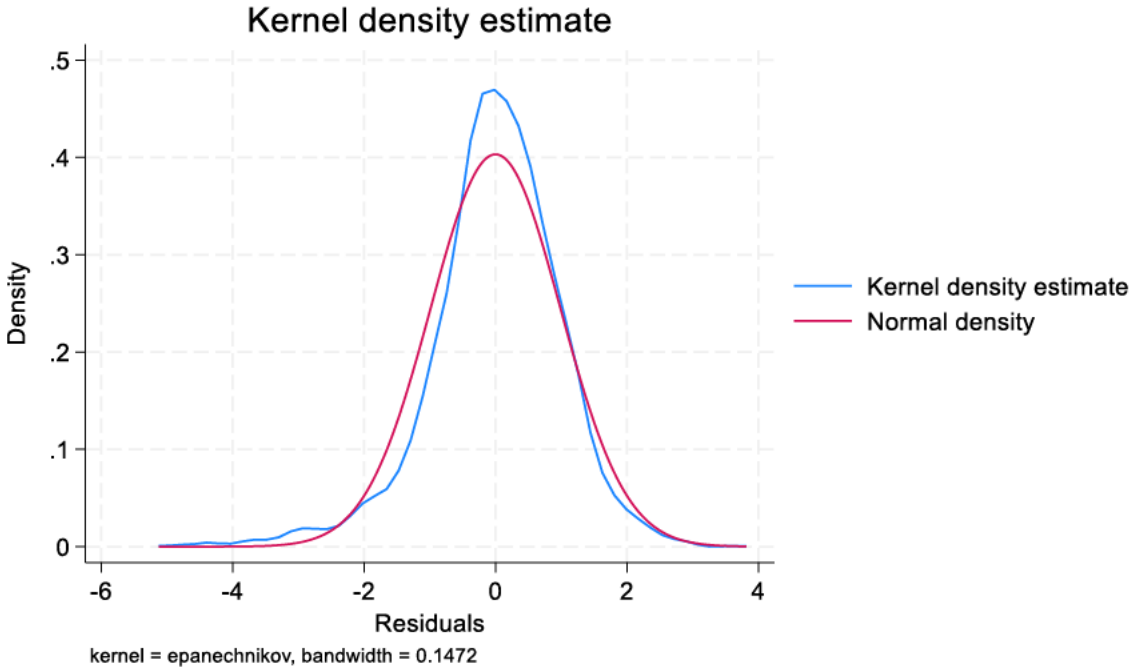

Figure 4-1: Normality of residual: Kernel density test for Model 3

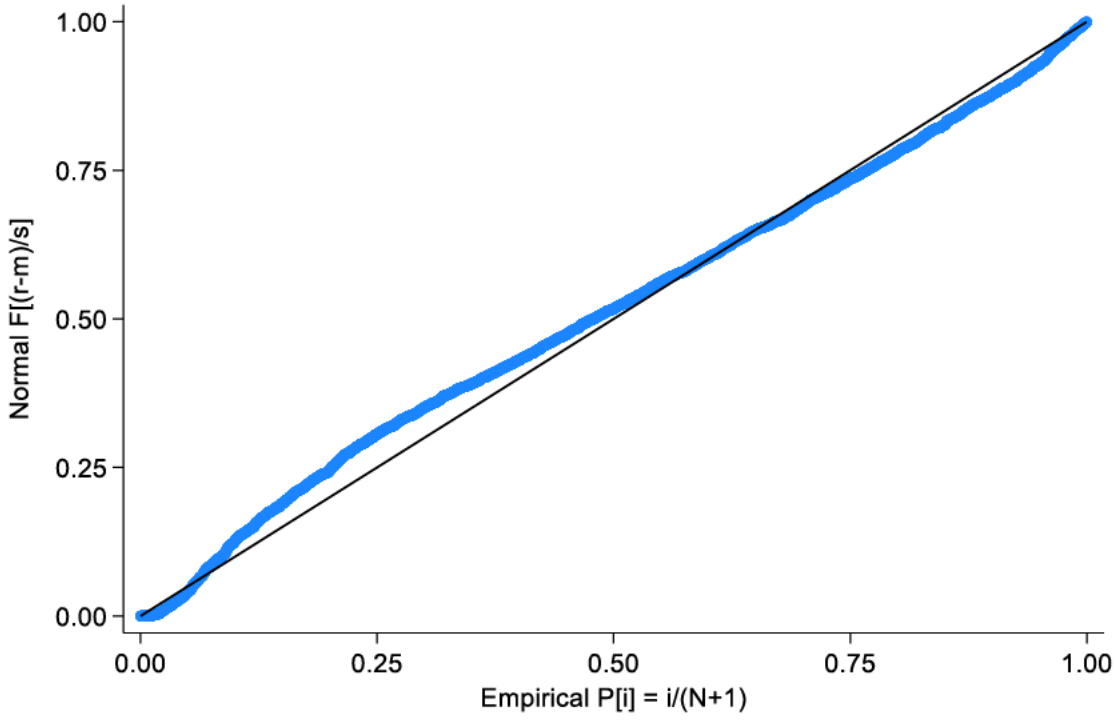

Figure 4-2: Normality of residual: Standardised P-P plot for Model 3

4.7.3 Maps

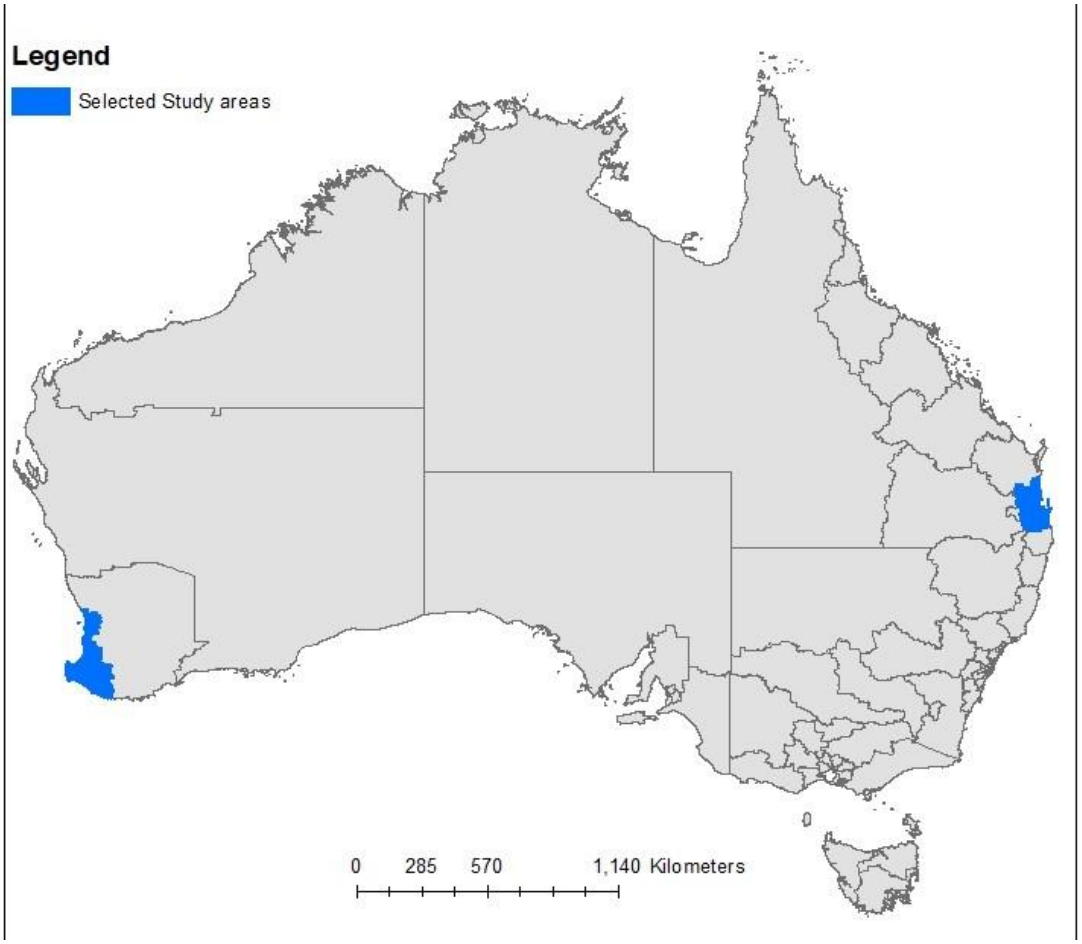

Figure 4-3: Selected study areas

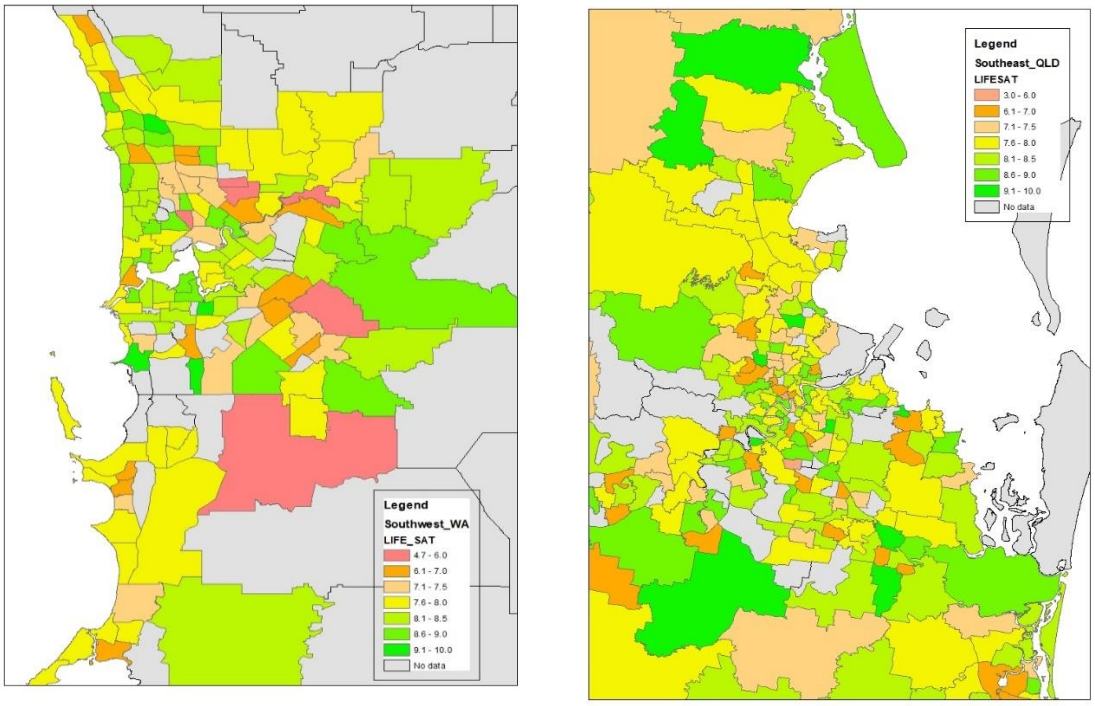

Figure 4-4: Average LS score by SA2 in metropolitan Perth and Brisbane (SEQ)

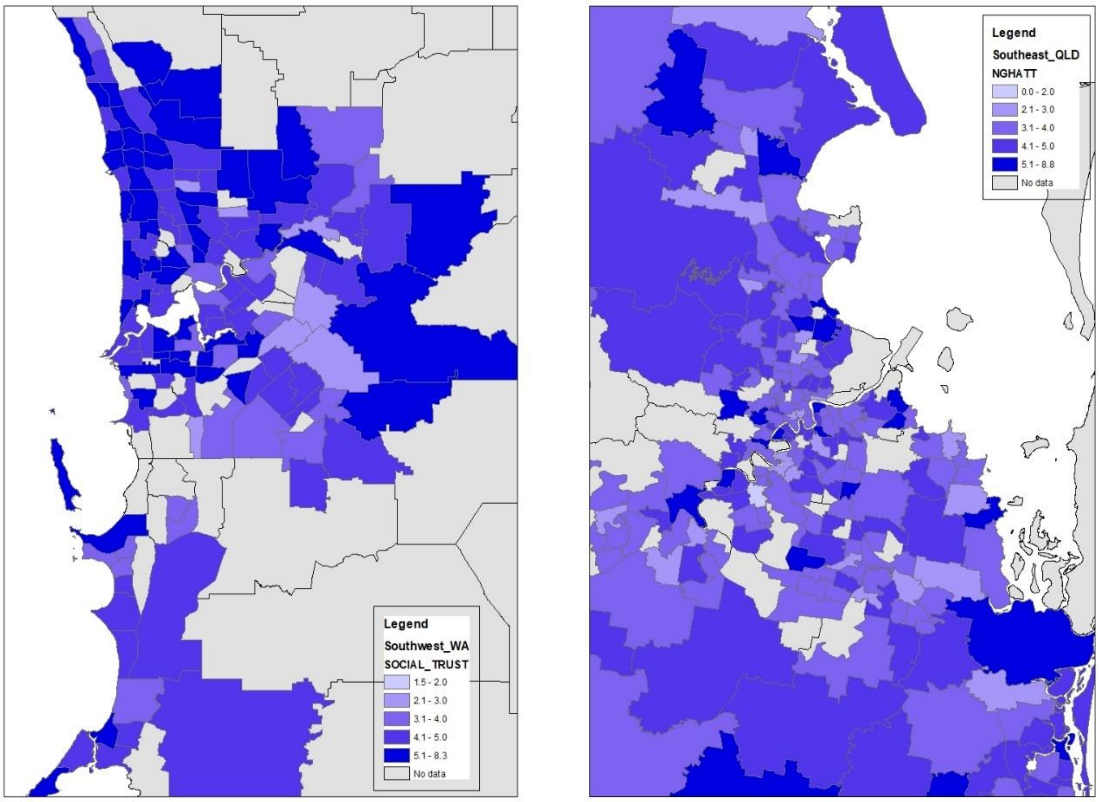

Figure 4-5: Average score for social trust by SA2 in metropolitan Perth and Brisbane (SEQ)

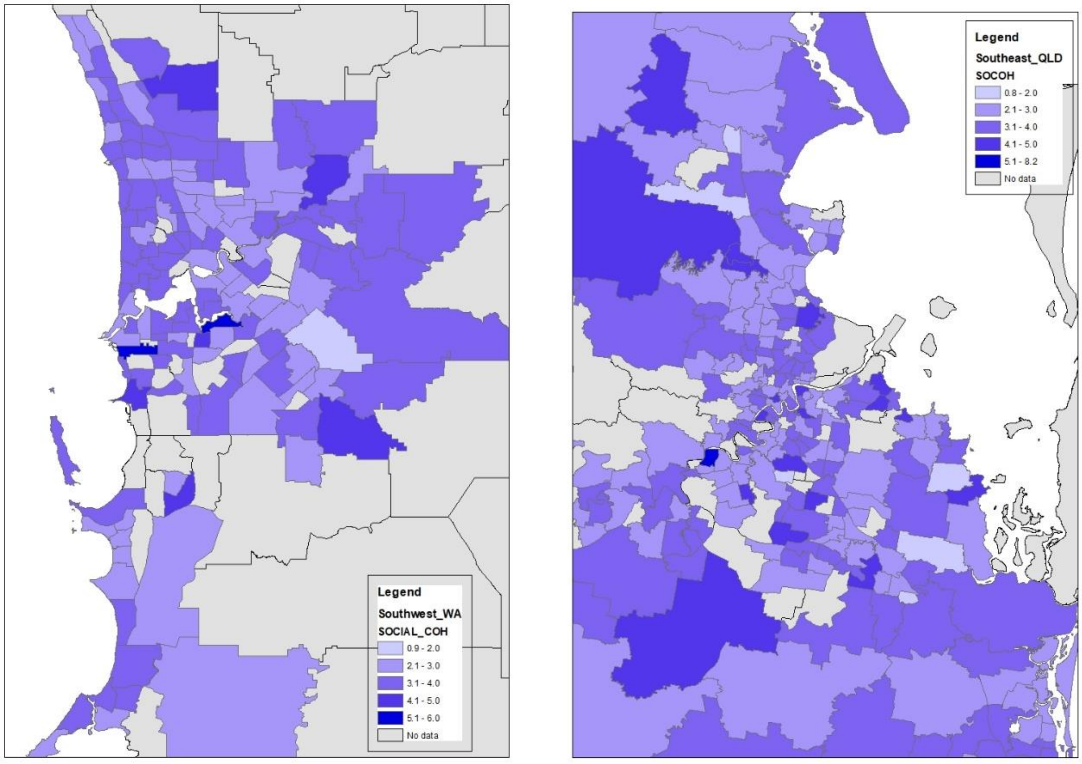

Figure 4-6: Average score for 'engagement and connection' by SA2 in metropolitan Perth and Brisbane (SEQ)

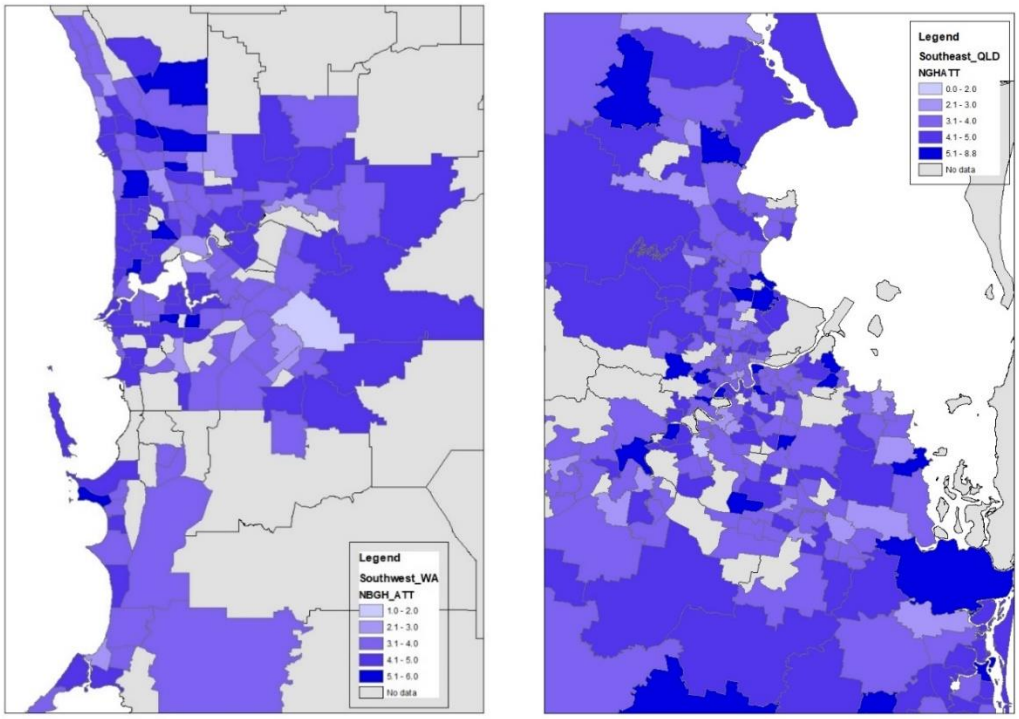

Figure 4-7: Average score for 'psychological sense of community' by SA2 in metropolitan Perth and Brisbane (SEQ)

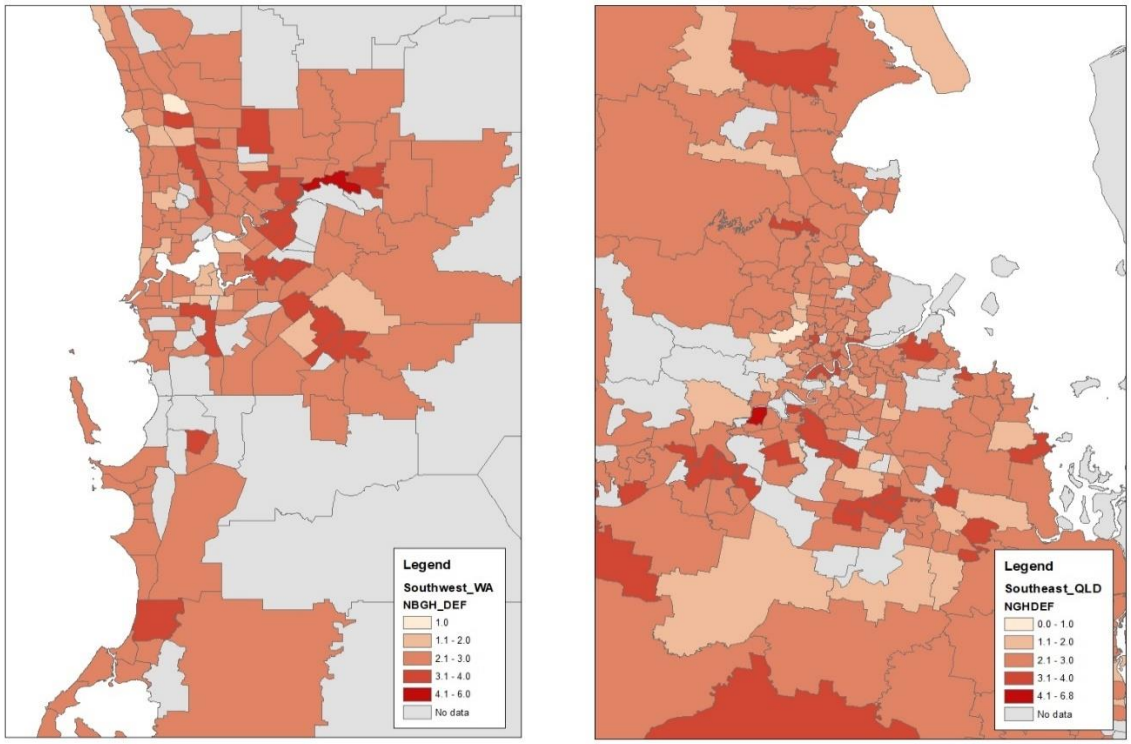

Figure 4-8: Average score for 'neighbourhood safety issues and shabbiness by SA2 in metropolitan Perth and Brisbane (SEQ)

Chapter 5 How does individual perception of local climate and environmental factors influence overall subjective wellbeing?

In this chapter, I address Research Objective #3 identified in Chapter 1 and explore how the perception of local climate and environmental factors impact individual life satisfaction. This general inquiry is structured around several questions which I address by analysing data collected through a customised survey. The study is an innovative exploratory investigation of the role of perceived climate characteristics and perceived environmental attributes in shaping subjective wellbeing. A better understanding of that process will inform policy that promote adaptation to local climate and environment conditions and emphasise the potential health and wellbeing benefits from enjoying the natural environment.

This chapter will be submitted as a manuscript[54] for a publication in a journal that has yet to be determined. The chapter has been edited from the draft submission manuscript to remove information already available elsewhere.

Abstract

Data from a survey conducted across different climatic regions of Australia is analysed using multiple stage linear regressions with the aim of providing proof of concept of this framework. The work provides insight into how individuals perceive their local environment and climate. Empirical evidence suggests that both the natural environment and the local climate contribute to subjective wellbeing, however little is known about *how* specific climatic conditions, and environmental attributes affect subjective wellbeing. The study develops a conceptual framework of analysis to address this question, building on prior wellbeing research. A series of research questions are stated, addressing each link within this framework. The results indicate that positive perceptions about the local climate and the local environment are associated with higher life satisfaction ratings. They also suggest that the

[54] Individual authors' contributions: P Lignier, conceptualisation, design, data collection, data analysis and manuscript writing; D Jarvis, project supervision, conceptual guidance and critical manuscript review; D Grainger: project supervision, technical guidance and critical manuscript review; T Chaiechi, project supervision and critical manuscript review.

level of satisfaction with the local climate and the local natural environment is dependent on specific perceived climate attributes and the perceived availability of environmental amenities. The analysis also reveals that the degree of association between objective climate indicators and subjective perception varies with the type of attribute (temperature, sunshine, rain) and the climate region. The findings will inform local policy initiatives that promote adaptation to local climate today and in the future, encourage outdoor activities and the enjoyment of the natural environment, and emphasise the health and wellbeing benefits that can be derived from this enjoyment.

5.1 Introduction

The importance of climate and nature to subjective wellbeing has been well documented[55], but little is known about *how* the local natural environment enriches our happiness and quality of life. More specifically, there is a key knowledge gap about how individual perception of specific attributes influence the overall subjective evaluation of the quality of the local environment and quality of life in general. This chapter presents an exploratory study that examines the process through which local climate and environment factors influence life satisfaction. A better understanding of that process will assist policy initiatives that support adaptation to diverse, and potentially changing, local climates, and promote the enjoyment of natural environment amenities.

Much of the research on subjective wellbeing in the field of economics has focused on identifying and measuring the impact of contributing factors; among these the contribution of the natural environment has been well canvassed in the empirical literature. Prominent issues include the enjoyment of specific environmental goods or services, and the impact of negative environmental externalities like pollution (Jarvis et al., 2023). For example, living close to greenspace (Ambrey & Fleming, 2013; Aoshima et al., 2018) has been found to increase wellbeing, whilst living in an area with high levels of air pollution may result in an adverse impact (Ferreira et al., 2013; Luechinger, 2009). The contribution of weather and climate factors has also been examined, albeit to a lesser extent, for instance the effects of the weather on mood and life satisfaction ratings (Connolly, 2013; Keller et al., 2005); the impact of various climate variables (Maddison & Rehdanz, 2011), and of extreme climate events (Calvo et al., 2015; Zander et al., 2019) on life satisfaction.

[55] For a review of the relevant literature on this topic, see Chapter 2, Section 2.3.3

Whilst there is enough evidence to support the assumption that both the climate and the natural environment impact individual wellbeing, we have little indication about how *local* climate attributes, and natural environmental amenities and dis-amenities contribute to individual wellbeing. The objective of this research is to explore this process. My inquiry starts with the development of a conceptual framework building on a similar framework used in wellbeing research; using this framework, it then proceeds through multiple stages. Firstly, I examine how subjective evaluations of the local climate and the local environment contribute to overall life satisfaction. Secondly, I investigate to what extent these subjective evaluations are impacted by individual perceptions of objective climate and environmental attributes. Thirdly, I assess the association between perceptions about local climate attributes and objective climate indicators. From this general objective, I derive several research questions around which the inquiry can be structured:

RQ_1: What is the impact of the subjective evaluation of the local climate on overall life satisfaction?

RQ_2: What is the impact of the subjective evaluation(s) of the local natural environment on overall life satisfaction?

RQ_3: How do perceived local climate attributes (cold, hot, rainy, windy, sunny) impact cognitive evaluation of the local climate?

RQ_4: How do perceived local environmental amenities and dis-amenities impact cognitive evaluation of the local environment?

RQ_5: How well do perceived local climate attributes (cold, hot, rainy, windy, sunny) match actual climate indicators?

RQ_6: Do perceived local climate attributes have a stronger association with overall life satisfaction than objective climate indicators?

The remainder of this chapter is structured as follows. I start with a brief review of the relevant literature (Section 5.2) before describing the methods used to collect and analyse the data for this research (Section 5.3). Results are reported in Section 5.4, a discussion follows in Section 5.5; finally in Section 5.6, I summarize the findings, discuss the limitations of the research, and outline the practical implications of the outcomes.

5.2 Literature review

5.2.1 Subjective perception and actual observations

The extent to which subjective perceptions match actual physical observations and whether subjective indicators are more relevant to wellbeing than objective indicators has been the subject of both theoretical debate and empirical research (Diener & Suh, 1997; Kubiszewski et al., 2018; McAllistair, 2005). Empirical evidence shows that subjective perceptions may diverge markedly from objective conditions (Schneider, 1975) revealing a degree of homeostasis that demonstrates the capacity of human beings to adapt to objective conditions unless those conditions exert a powerful negative influence (Cummins, 2000). An example of this complex relationship is illustrated by the association between income and wellbeing. While extreme poverty is often associated with unhappiness, the relative income effect that takes into account individual perception of one's financial position relative to others or to previous positions is more relevant in explaining differing levels of satisfaction with life than objectively measured income (Clark et al., 2008; Killingsworth, 2021).

To the best of my knowledge, all studies that examined the influence of climate variables on subjective wellbeing have considered actual climatological observations rather than individual perceptions. Both subjective perceptions and actual indicators of environmental amenities such as greenspace and dis-amenities such as air pollution have been investigated with evidence showing some divergence between perception and reality (Hur et al., 2010).

5.2.2 Perception of weather and climate

Perceptions of the weather, in particular the association between outdoor temperatures and thermal sensations, is the focus of an abundant literature in the field of biometeorology that is outside the scope of this chapter. The upshot from that research is that divergent perceptions of comparable thermal conditions can be explained by physiological factors such as gender and age and psychological factors such as previous experience, expectations and attitude (Lindner-Cendrowska & Blazejczyk, 2018).

While the perception of transitory *weather* is a sensory (hedonic) experience, the perception of *climate*[56] is a cognitive experience that involves (evaluative) judgement based by statistical baselines, but also influenced by personal experiences, memory, and social learning from previous generations (Howe & Leiserowitz, 2013; Hulme et al., 2009). The

[56] The distinction between climate and weather was discussed in Chapter 2, Section 2.3.3.2, note 17.

literature provides little evidence about how people evaluate normal climate conditions in their local area: people who live in urban areas are often insulated from surrounding climate conditions and therefore pay little attention to them (Hitchings, 2011); conversely people living in rural areas or engaged in occupations that require attention to the local weather (farming, fishing) are more aware of weather patterns (Harter et al., 2012; Meze-Hausken, 2004). People seem to notice when weather conditions deviate from the norm, and there is a broad coincidence between seasonal climate perceptions and temperature and precipitation anomalies (Howe & Leiserowitz, 2013). However, cognitive projection bias may lead respondents to outweigh their most recent experience as more salient and representative of a large trend period (Hansen et al., 2012). In some cases, motivated reasoning, e.g., pre-existing beliefs about climate change (e.g., whether or not climate change is really happening), may bias recollection about seasonal climate in a way that fits with those pre-existing beliefs (Howe & Leiserowitz, 2013; Kahan, 2013).

5.2.3 Weather, mood, and the rating of life satisfaction

Research into the effects of weather on mood and cognitive abilities shows that time spent outdoors reinforces the relationship between weather conditions (temperature and sunlight), mood, and cognitive abilities (Keller et al., 2005). Season and climate appear to act as moderating factors: high temperatures improve mood during spring time and in cooler climates but have the opposite effect during summer and in hotter climates (Keller et al., 2005). Overall low temperatures seem to increase positive affect and decrease negative affect, but men do not appear to respond to weather shocks as much as women (Connolly, 2013). Findings from a longitudinal study in Japan suggest that happiness and *positive* affect are maximised when the current temperature is around 14°C while weather conditions have apparently no significant influence on *negative* affect (Tsutsui, 2013).

The influence of current weather conditions on subjective LS evaluation is ambiguous. According to Connolly (2013) precipitation and high temperatures have a negative effect on reported LS scores; however Levinson (2009) reach the opposite conclusion, while Lucas and Lawless (2013) see little evidence of association. Other studies show that cloudiness is associated with lower LS ratings (Barrington-Leigh, 2008), and conversely solar exposure has a positive influence, while barometric pressure and wind speed have a negative effect (Feddersen et al., 2016).

5.2.4 Climate observations and life satisfaction

Empirical evidence shows that temperature measures (average, extreme or duration) are the climate attribute with the most significant influence on average LS; however, the impact is conditioned by the season and the type of climate where the person lives. An increase in average temperatures during colder months has a positive effect on LS, while a similar increase during hotter months has a negative effect (Brereton et al., 2008; Frijters & Van Praag, 1998; Rehdanz & Maddison, 2005). Similarly, warmer temperatures make people who live in a cool climate happier, but people who live in a hot climate less so (Maddison & Rehdanz, 2011).

The amount and frequency of precipitation does not generally affect wellbeing (Maddison & Rehdanz, 2011; Murray et al., 2011), with a few exceptions (Brereton et al., 2008); however prolonged periods without rain have been linked to reduced LS in the United States and other countries (Berlemann & Eurich, 2021a; Rehdanz & Maddison, 2005). The combined effect of cold temperatures and strong wind (windchill effect), and high temperatures and humidity (stickiness) have a significant negative influence on reported LS (Frijters & Van Praag, 1998). Lastly, extreme climate events such as severe droughts, floods, prolonged hot or cold weather, and cyclones are associated with a long term negative impact on LS (Berlemann & Eurich, 2021a, 2021b; C. J. Fernandez et al., 2019; Kraehnert & Fluhrer, 2021; Osberghaus & Kuhling, 2016).

5.2.5 Perception of the natural environment and life satisfaction

The beneficial impact of the natural environment on human health is well documented: people living close to greenspace have fewer self-reported negative health symptoms (de Vries et al., 2003) and have lower cortisol levels (less stress) (Thompson et al., 2012) while those who walk outdoors are significantly happier (Nisbet & Zelenski, 2011). More broadly, we have strong evidence that access to greenspace or even proximity to greenspace enhance wellbeing (Ambrey & Fleming, 2013; Aoshima et al., 2018; Bertram & Rehdanz, 2015); but it is not clear that people living in a rural or remote area are happier than those living in an urban setting (Gilbert et al., 2016; Jarvis et al., 2023). Crucially, the perceived amount of greenspace, the subjective quality and satisfaction with greenspace are often more closely related to LS than objective reality (Hur et al., 2010; Kothencz & Blaschke, 2017). Other environmental amenities such as proximity to water (Brereton et al., 2008; Wheaton et al., 2020); engagement with nature (Biedenweg et al., 2017) or proximity to an environmental conservation area (Jarvis et al., 2017) have been linked to higher levels

of wellbeing, while actual or perceived presence of pollution have an adverse effect (Liao et al., 2015; Luechinger, 2009; MacKerron & Mourato, 2009; Rehdanz & Maddison, 2008).

5.2.6 Research gaps and conceptual framework

In summary, the literature provides clear evidence that weather and climate are perceived differently depending on physiological characteristics, personality, and personal circumstances. Current weather conditions influence mood, but the impact of weather on the cognitive evaluation of LS is contested. Temperature, particularly extreme temperature, is the climate attribute most likely to affect individual wellbeing, but little is known about how specific climate attributes are perceived by individuals and how this could impact their cognitive evaluation of the local climate. There is also strong evidence that the natural environment, through its perceived qualities or deficiencies impacts LS, however we are missing a holistic investigation of the overall impact of the local natural environment on wellbeing.

Given that the investigation of the above research gaps is exploratory in nature, I needed to develop a customised framework of analysis appropriate for the purpose of this study. To this end, I build upon a framework originally developed by Mouratidis (2018) to analyse how built environments influence subjective wellbeing (SWB). This original framework integrates and links together neighbourhood characteristics including both perceived characteristics and objective indicators, the three dimensions of SWB[57], and mediating factors that explain how neighbourhood characteristics impact on wellbeing (Mouratidis, 2018). An essential feature of that framework is that it uses a multi-stage regression approach. In the first stage, LS, and other components of SWB are regressed against SWB determinants that include neighbourhood satisfaction as well as other predictors of SWB such as satisfaction with health, relationships, and financial situation. The second stage involves the regression of neighbourhood satisfaction against factors including objective and perceived neighbourhood characteristics. Socio-demographic factors are used as control variables for both stages of regression (Mouratidis, 2018, 2019). Mouratidis's framework of analysis provides a good foundation for the present topic of investigation as both studies investigate the influence of local contextual characteristics (climate and natural environment in this study, neighbourhood characteristics in Mouratidis's research) on SWB, while controlling for socio-demographic factors. Apart from the different focus, there are two

[57]The dimensions of SWB were discussed in Chapter 2, Section 2.2.2.

main differences between the adapted framework used for this study (Figure 5-1) and the original (Mouratidis, 2018, p. 32 Figure 1). Firstly, the framework has been simplified, in that I only consider one dimension of SWB: LS. The second difference is that I add a further stage of analysis by exploring the relationship between climate perception and actual climate observations. One the main benefit of this framework of analysis is that it allows the integration of both objective and subjective factors contributing to wellbeing as discussed in Section 5.2.1.

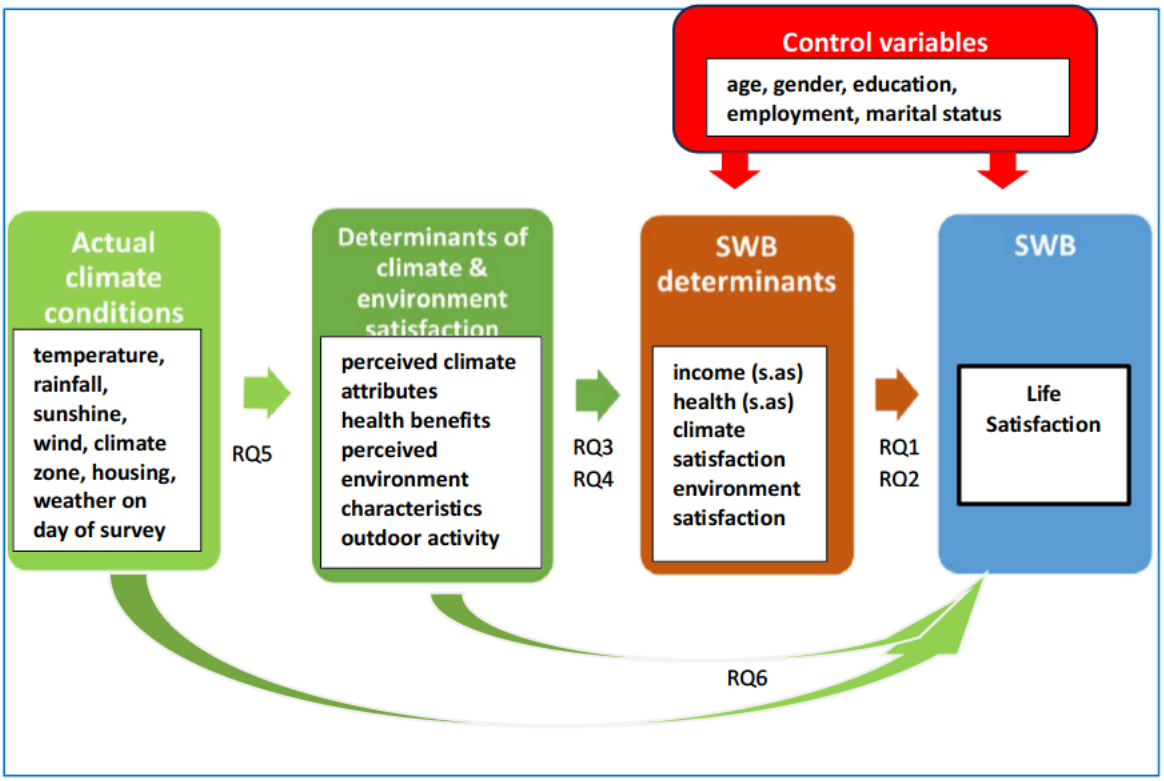

Figure 5-1: Conceptual framework of analysis

Adapted from Mouratidis (2018, p.32, Figure 1)

5.3 Methods

5.3.1 Method of analysis

It is important to note that a covariance based Structural Equation Modelling (SEM) approach was initially conducted to answer the research questions identified in Section 5.1. However, upon further deliberation, this was abandoned given that SEM is predominantly used to represent causal relationships (Ramlall, 2017) and covariance based SEM would not be appropriate here considering the exploratory nature of the study (Dash & Paul, 2021). Further, latent constructs, a key feature of the SEM approach (Ramlall, 2017), were not

considered relevant to this study. Instead, a regression-based approach as featured in the conceptual framework set out in Section 5.2.6 was considered more appropriate.

The framework includes successive (multi-stage) linear regressions addressing the specific research questions as shown in Figure 5-1. In the first stage, LS is the dependent variable, while LS determinants and control variables are the explanatory variables. In the second stage, two separate regressions examine the relationship between climate satisfaction and environment satisfaction and their respective determinants. In the third stage, separate linear regressions model the relationship between specific perceived climate attributes and corresponding objective climate conditions. In the final stage, two separate regressions examine the association between LS and perceived climate characteristics; and LS and actual climate observations while controlling for other factors.

5.3.2 Data collection

5.3.2.1 Survey design

A customised electronic survey was developed to collect the data for this study. To capture a wide variety of climate influences on individual perceptions, the survey was targeted at climatically diverse regions within Australia. The sampling frame for the survey was built from lists of publicly available emails and residential addresses acquired from a commercial provider. Separate lists were acquired for states corresponding to different climate zones: Tasmania/ Victoria[58] (cool temperate), Queensland[59] (sub-tropical/ tropical) and Western Australia (WA) (warm temperate). A dual distribution mode was adopted for this survey including a broadcast of invitations by email and a mailout of invitation postcards with a QR Code link to the electronic survey website (*Qualtrics*).[60]

A specific methodology was implemented for the selection of participants to be included in the postal mailout sample as pure random sampling from the list of residential addresses would have resulted in large population centres being over-represented. This outcome would be undesirable considering the existing evidence that rural people are more impacted by weather and climate than those in urban areas. *Cluster sampling* was used to

[58]As the number of responses received from Tasmania was considered too low, a limited additional number of observations were sourced from regional Victoria. Whilst the climates of Victoria and Tasmania are not identical, they can both be classified as cool temperate.

[59]The Darling Downs region in Southern Queensland was classified as 'temperate'.

[60]The survey design and the rationale for its adoption were comprehensively discussed in Chapter 2, Section 2.7.2.

select the final sample of participants; this involved a two-stage process: 1) identification of clusters representing specific climatic regions; 2) selection of participants within each cluster (Neuman, 2000, p. 209). The agroecological framework developed by the CSIRO was retained for this process (Williams et al., 2002). After eliminating sparsely populated areas, five sampling clusters were selected for the sub-tropical/ tropical region and three for the temperate region. Within each cluster, the random selection process was completed by assigning random numbers using the *Rand Excel* function (see Tables 5-7 and 5-8 Appendix A for further details about mailout sample selection). A total of 1,000 postcard invitations were sent to Tasmania and 2,000 to Queensland.[61]

5.3.2.2 Questionnaire design and survey implementation

The main purpose of the survey instrument was to collect data regarding individual perceptions about the local climate and the local environment. Respondents were also invited to evaluate their overall LS using a 0 to 10 scale. Together with secondary data on actual climate, this provided the key information required for a preliminary proof of concept of the conceptual framework. The questionnaire was designed so that it would be easy to understand; it would be accessible through either a computer, a tablet, or a smartphone; and take no more than 10 minutes to complete. Structure and wording of questions were kept as close as possible to the wording of equivalent questions in the HILDA survey to facilitate comparisons of the results. An initial pilot survey gave us the opportunity to improve the wording and amend the ordering of some questions.[62]

The survey was distributed in two waves: one in Winter and one in Summer between August 2021 and June 2022.[63] This two-wave strategy is justified on the ground that the season could influence responses (Brooks et al., 2017; Keller et al., 2005). Email broadcast and collection of data were managed through *Qualtrics* with the use of an anonymous link.

[61]Western Australia was not retained for the mailout mode due to the distance from the researcher's location, and the fact that the state was subject to border closures at the time of the mailout.

[62]Ethical approval was obtained for this research from the Human Research Ethics Committee at James Cook University (Approval ID H8397).

[63]The WA survey was sent separately once COVID-19 borders restrictions were removed. It was believed that the presence of a hard border limiting the movements of people to and from WA might be a limiting factor restricting the comparability of the WA results with the east coast.

A total of 295 usable responses were collected and the response rates for Tasmania and Queensland were around 1.25% for the email broadcast and 2.6% for the mailout (See Tables 5-9 and 5-10, Appendix B), comparable to the results for Australian surveys using similar methodologies (Sinclair et al., 2012). The lower email response rate for WA (0.5%) may be attributable to the difference in demographics due to the inclusion of Metropolitan Perth in the sample: Perth represents a more urban population with a larger proportion of people where English is not the first language making survey completion more difficult.

Wave analysis (Lankford et al., 1995) was used to test whether the mode of contact or the season when the survey was administered introduced bias in survey responses. Test results (See Appendix C for further details about this process) revealed that responses to key questions were statistically independent of either the mode of survey contact or the season when the questionnaire was administered.

5.3.3 Variables

In addition to the data collected by the survey instrument, secondary climate observations sourced from the Australian Bureau of Meteorology (BOM) for the 2000-2020 period were compiled to determine average climate conditions at the location where the respondent resides. *ArcGIS* (Geographic Information System) was used to map the locations of respondents thanks to coordinates recorded with the response.[64] The use of a proximity GIS tool allowed the identification of the nearest weather station from the respondent's location. Data about the weather at the time the survey was completed (recorded by the survey instrument) were collected using the same process.

Perceptions about local climate conditions were captured by asking respondents to rate their level of agreement (1-5) with specific propositions such as "it is too hot in summer where I live". Evaluation of the local climate was based on the selection of the statement that best described how the respondent "…feels about the climate where they live". Six options ranging from 'awful' to 'fantastic' allowed participants to rank their satisfaction. Outdoor activities were assessed by their frequency from 'not at all' to 'every day'. Data about local environmental amenities and dis-amenities are based on self-reporting using level of agreement (1-5) with statements such as "I live within walking distance from greenspace". Finally, evaluation of the local natural environment (meant to refer to greenspace and natural scenery) was assessed by asking respondents to identify various wellbeing benefits from the

[64] A check was completed to ensure that the location recorded matched the postcode of residence.

natural environment from a list provided. The list of variables used for this study is shown in Table 5-11 Appendix C.

Socio-demographic control variables represented in the framework in Figure 5-1 were selected with guidance from the LS literature. Variables identified as having an impact on SWB and LS include age, gender, education level, marital status, and employment status.[65] SWB determinants other than climate satisfaction and environment satisfaction were self-assessed income status and self-assessed health status that mirror similar variables used in the original model. In addition, Mouratidis (2018) had 'satisfaction with relationship' as one of the SWB determinant. This factor was not retained as a determinant in this study, because of its close association with 'marital status', one of the control variables.

5.3.4 Regression models

Specific regression models are developed to represent the relationships in each stage of the conceptual framework. To investigate the relationship between LS and the control variables, I develop the model below:

$$Y_i = \beta_o + \beta_1 X_i + \varepsilon_i \text{ (Model 1)}$$

where Y_i is LS for individual i, X_i is vector of variables representing individual attributes and ε_i is an error term.

Model (1) can be extended to include LS determinants representing domain specific satisfaction:

$$Y_i = \beta_o + \beta_1 X_i + \beta_2 S_i + \varepsilon_i \text{ (Model 2)}$$

where S_i is a vector of variables representing domain specific satisfaction; this includes satisfaction with the local climate and satisfaction with the local environment *inter alia*.

This model addresses research questions RQ_1 and RQ_2 about the impact of local climate satisfaction and local environment satisfaction on LS.

I then focus on the next stage in the conceptual framework which is about the relationship between climate and environment satisfaction and their determinants. The following equation (Model 3) models the relationship between climate satisfaction and perceived local climate attributes, controlling for socio-demographic factors and addresses research question RQ_3:

[65] Refer to Section 2.3.2.3 in Chapter 2 for a full discussion of the evidence about the influence of these factors on LS.

$$S_{ci} = \gamma_o X_i + \gamma_1 P_i + \gamma_2 a_i + \varepsilon_i \text{ (Model 3)}$$

where S_{ci} is the climate satisfaction score for individual i, X_i is a vector of individual attributes variables, P_i is a vector of variables representing perceived local climate characteristics, a_i is the outdoor activity score[66] and ε_i is an error term.

Equation (Model 4) models the relationship between satisfaction with the local environment and perceived characteristics of the local natural environment, controlling for socio-demographic factors and addresses research question *RQ4*:

$$S_{ei} = \gamma_o X_i + \gamma_1 E_i + \gamma_2 a_i + \varepsilon_i \text{ (Model 4)}$$

where S_{ei} is the environment satisfaction score for individual i, and E_i is a vector of perceived environment characteristics.

Equation (Model 5) models the third stage in the multi-stage regression framework: i.e., the relationship between perceived climate characteristics and actual climate observations and addresses research question *RQ5*. The model also incorporates variables representing weather conditions at the time of the survey and housing thermal characteristics.

$$P_{ki} = \delta_0 + \delta_1 c_{kj} + \delta_2 w_{kj} + \delta_3 h_i + \varepsilon_i \text{ (Model 5)}$$

where P_{ki} is perceived climate characteristic k by individual i, c_{kj} is the actual observation for corresponding climate attribute k in area j, w_{kj} is the present condition of attribute k in area j at the time of survey and h_i is the relevant house thermal attribute for individual i .

Finally, I address research question *RQ6*, by comparing the association between LS and perceived climate characteristics (Equation (Model 6)) and LS and actual climate indicators (Equation (Model 7)). In both models, I control for the influence of other LS determinants.

$$Y_i = \beta_o + \beta_1 X_i + \beta_2 S_i + \gamma_1 P_i + y_2 E_i + \gamma_3 a_i + \varepsilon_i \text{ (Model 6)}$$

$$Y_i = \beta_o + \beta_1 X_i + \beta_2 S_i + \gamma_1 E_i + \gamma_2 a_i + \delta_1 c_{kj} + \delta_2 w_{kj} + \delta_3 h_i + \varepsilon_i \text{ (Model 7)}$$

For all estimations, I treat attitudinal responses as continuous variables[67]. I checked for heteroskedasticity and normality of residuals for each of these models. Considering the limitations applying to the validity of formal tests such as the Breusch Pagan and Shapiro

[66] The activity score is described in further detail in Section 5.4.2.1 below.

[67] See Chapter 2, Section 2.8.1 for a comprehensive discussion of this issue.

Wilk tests (Olvera Astivio & Zumbo, 2019), I also relied on visual tests such as the kernel density test and the P-P plot test.

5.4 Results

5.4.1 Sample representativeness

Sample socio-economic averages were compared to reference indicators for the different source populations: Tasmania, Queensland, and WA (Table 5-1). Respondents in the sample are on average older; males and people with a university degree are over-represented; they are more likely to be married or in a de-facto relationship and their household income is higher. This deviation in demographic characteristics between the sample and the reference populations may induce some bias in the survey responses and therefore interpretation and extrapolation of results should be made with caution. This issue is systematically addressed in the discussion section (Section 5-5). It is also acknowledged that the inclusion of the Perth region in the WA sample, could influence the interpretation of the WA results compared to the east coast that does not include respondents from large metropolitan areas.

Table 5-1: Comparisons of key demographic indicators: sample and source populations

	Sample	**Tasmania**	**WA**	**Queensland [a]**
Mean age [b]	54	42	38	41
Household income [b]	$96,424	$70,616	$90,972	$81,375
Proportion of males [b]	57.5%	49.1%	49.7%	49.5%
Proportion married /de facto [b]	71.1%	57.8%	59.6%	59.6%
Proportion with a univ. degree [c]	58.5%	16.2%	20.5%	12.7%
Proportion unemployed [d]	6.1%	5.1%	3.1%	4.8%
Proportion who owned their house [e]	70.1%	70.1%	69.2%	65.3%

[a] Queensland: sampled SA4 population (Central Qld, Mackay-Isaac-Whitsunday, Townsville, Cairns, Wide Bay, Sunshine Coast and Darling Downs)

[b] Source: ABS Quick Stats 2021 census, Australia: https://www.abs.gov.au/census/find-census-data/quickstats/2021/5GPER. Accessed 7/7/2022

[c] Source: ABS, 2016 Quick Stat, Australia: https://www.abs.gov.au/census/find-census-data/quickstats/2016/5GPER Accessed 7/7/2022

[d] Source: ABS Labour force Australia, May 2022: https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia/latest-release#states-and-territories

5.4.2 Descriptive statistics

5.4.2.1 Life satisfaction and determinants of life satisfaction

The mean LS score for the sample is 7.56 (on a 0 to 10 scale), somewhat lower than the results obtained in previous Australian research based on HILDA data[68] (Table 5-2). Possible reasons for lower LS scores in this survey include the higher proportion of highly educated respondents and the high proportion of males, both indicators being negatively associated with LS (Kubiszewski, Zakariyya, et al., 2019). The lower LS rating could also be attributed to the effects of the COVID-19 pandemic, still present in the country at the time of survey.

Self-assessed factors include socio-demographic characteristics such as wealth status, health status as well as level of outdoor activities. The mean ratings are 3.23 for wealth status and 3.32 for health status (1 to 5 scale) indicate that on average respondents perceived themselves as relatively healthy and assessed their financial situation as 'reasonably comfortable'. The overall outdoor activity score (based on the frequency ratings of 12 specific activities) is 19.3 out of 60. The most frequently performed outdoor activities are 'walking as part of domestic activities (4.1 out of 5) 'recreational walking' (3.3) and 'gardening and beekeeping' (3). The overall satisfaction with the local climate is relatively high with a mean score of 4.7 (1-6 scale) and a low standard deviation (1.13).

Satisfaction with the natural environment is measured by a summative variable representing the number of wellbeing benefits from the environment identified by the respondent rather than a Likert scale self-rated evaluation. This choice was guided by the view that the complexity of interaction between the natural capital and subjective wellbeing (See Figure 2-3, Chapter 2) could not be adequately captured by a single score on a Likert scale (Jarvis et al., 2023). The average score for this variable is relatively low (3.02 on a 0 to 7 scale) with a high degree of dispersion around the mean (SD= 2.36). The most frequently identified wellbeing benefits are "The local natural environment…"; "…relieves stress" (54% of respondents); "…encourages to exercise" (50%) and "…gives me a sense of place" (46%) (Figure 5-2).

[68] Mean overall LS scores from HILDA surveys between 2011 and 2016 were consistently between 7.9 and 7.95 (Kubiszewski et al., 2018, pp. Fig. 1, p. 363).

Table 5-2: Mean values for life satisfaction and determinant of life satisfaction

N=295			
Variable:	**Scale**	**Mean score**	**Standard deviation**
Overall life Satisfaction	0-10	7.56	2.14
Self-rated wealth status	1-5	3.23	0.80
Self-rated health status	1-5	3.32	1.11
Satisfaction with local climate [a]	1-6	4.69	1.13
Satisfaction with local environment [b]	0-7	3.02	2.36
Outdoor activity score	0-60	19.3	8.32

[a] Scale for climate satisfaction included 6 options from 1'the climate here is awful' to 6 'the climate here is fantastic'. For other variables, scale was from 1 'Strongly disagree' to 5 'Strongly agree'.

[b] Measured by the number of reported wellbeing benefits from the local environment

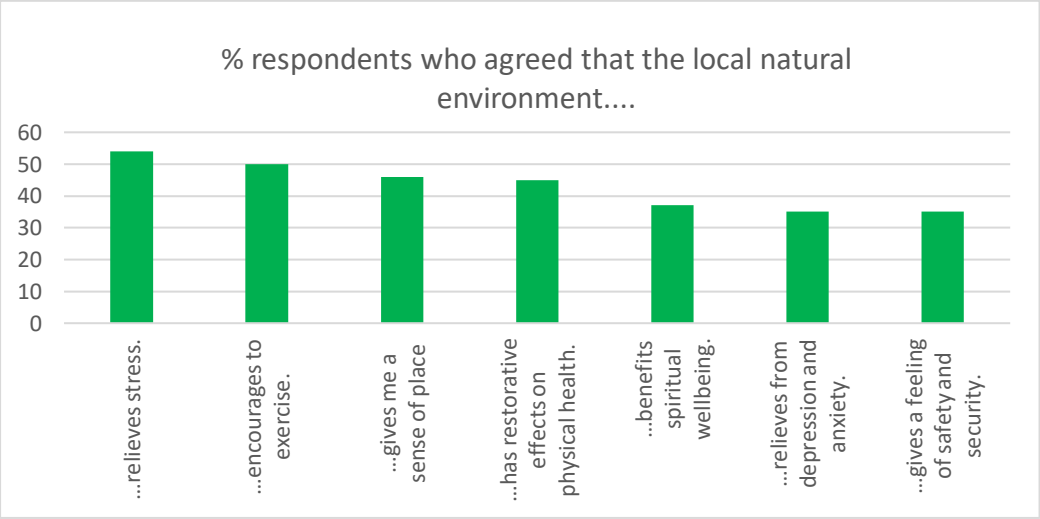

Figure 5-2: Percentage of respondents perceiving wellbeing benefits from the natural environment

5.4.2.2 Perceived local climate and local environment characteristics

Means scores for perceived local climate attributes suggest that the perception that it is 'too hot' is rated higher than the perception of 'too cold' (Figure 5-3). The relatively high standard deviation values suggest that perceptions about specific climate attributes vary across climate regions reflecting local conditions; however, the perception about sunniness is particularly high (4.16 on 1-5 scale) with moderate dispersion around the mean (SD=1.02). There is a relatively strong opinion among respondents that the local climate benefits both their physical and mental health (3.98 on 1-5 scale) with moderate dispersion around the mean (SD= 1.02).

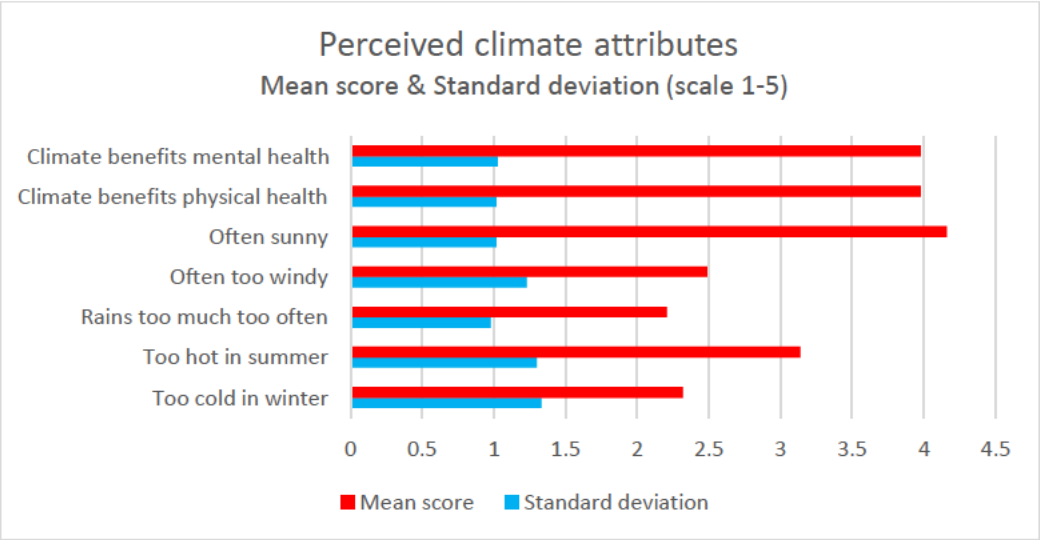

Figure 5-3: Perception of local climate attributes

Overall, respondents perceive low levels of environmental 'ills' in their local area with an average level of agreement around 2 (1-5 scale). Conversely, there is a high level of perception (4 and above) of environmental 'good' such as greenspace, safe walking tracks, conservation areas and beautiful scenery (Figure 5-4).

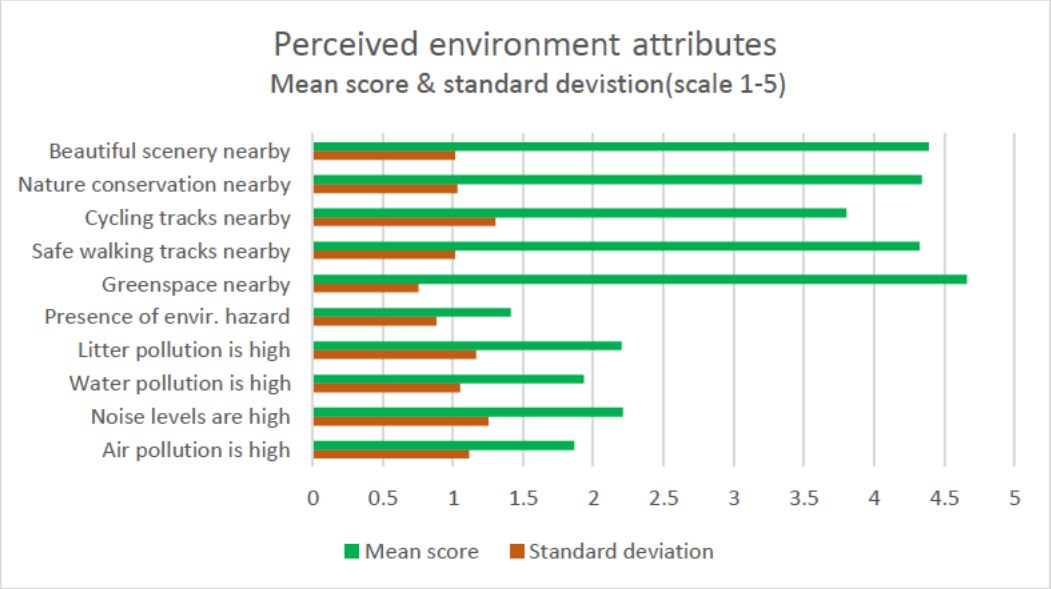

Figure 5-4: Perception of local environment attributes

5.4.3 Determinants of life satisfaction

Results for Models 1 and 2 (Table 5-3) show that control variables explain only a small part of the variations in LS. When the four LS determinants (self-assessed health, self-assessed wealth, climate satisfaction and wellbeing satisfaction) are added, the proportion of LS variations explained by the model increases significantly (from adjusted R^2=0.113 to adjusted

R^2=0.446); the predictive power of the model also improves (from AIC[69]=1178.9 to AIC=1026.2) even though we introduced more explanatory variables. The coefficients for all four LS determinants are significantly positive with climate satisfaction being comparable to health and wealth. The influence of environment satisfaction while positive and significant is not as strong. Among the control variables, only age (squared) remains significantly positive when satisfaction variables are included.

Table 5-3: Results for Model 1 and 2: determinants of LS

	Model 1			**Model 2**		
DV:	**LS**			**LS**		
N	276			268		
adjusted R^2	0.113			0.446		
AIC	1178.9			1026.2		
variables:	Coeff	CI		Coeff	CI	
wealth (self-assessed)				**0.676*****	0.402	0.950
health (self-assessed)				**0.649*****	0.446	0.851
climate satisfaction				**0.539*****	0.357	0.722
environment satisfaction				**0.107****	0.018	0.196
female	-0.164	-0.652	0.324	-0.227	-0.630	0.176
Ages (square)	**0.027*****	0.012	0.041	**0.020*****	0.008	0.032
married	**0.679****	0.143	1.216	0.077	-0.366	0.521
higher educ.	0.054	-0.438	0.546	-0.182	-0.584	0.219
unemployed	**-2.149*****	-3.259	-1.040	-0.395	-1.321	0.531

level of significance: *** p<0.01 ** p<0.05 * p<0.1

5.4.4 Determinants of climate and environment satisfaction

Model 3 and 4 regress climate and environment satisfaction against their potential predictors. In Model 3, I use a two-stage OLS regression model where 'health climate benefit' is treated as an endogenous variable with 'sunny' and 'outdoor activity score' used as instrumental variables. The results (Table 5-4) show that a relatively high proportion of the DV (climate satisfaction) variations are explained by the model (adjusted R^2=0.375). Perceiving health benefits from the climate is an important positive predictor of climate satisfaction. A perception that the climate is sunny is an important contributor of perceiving health benefits. The perception that the climate is too hot is a significant *negative* contributor of climate satisfaction, while the perception that the climate is too cold is also a negative predictor but with a smaller effect. Among control variables, being unemployed is a significant negative contributor of climate satisfaction.

[69] Akaike Information Criterion (AIC): See Chapter 3, note 7 for further information about this measure.

The proportion of the DV (environment satisfaction) variations explained by Model 4 is lower than for Model 3 (adjusted R^2=0.294). The main positive contributors to environment satisfaction are 'being female' and 'perceived presence of beautiful scenery'. Individuals who engage in frequent outdoor activities are also more likely to be satisfied with the local environment. The presence of green walking tracks has a small positive influence, while noise pollution has a small negative impact.

Table 5-4: Results for Models 3 and 4: determinants of climate satisfaction and environment satisfaction

	Model 3			**Model 4**		
DV	**climate satisfaction**			**environment satisfaction**		
adjusted R^2	0.375			0.294		
AIC [a]	-			1169.3		
n	278			275		
variables	Coeff	CI		Coeff	CI	
climate health ben. (end)	**0.392*** **	0.138	0.646			
too_hot (p)	**-0.202*** **	-0.295	-0.108			
too_cold (p)	-0.088*	-0.188	0.012			
rainy (p)	-0.035	-0.160	0.091			
windy (p)	-0.067	-0.171	0.037			
sunny (p) (inst.)	**0.452*** **	0.343	0.561			
outdoor_score (inst.)	0.010	-0.003	0.022			
female	-0.178	-0.395	0.039	**0.917*** **	0.408	1.426
age (square)	0.002	-0.004	0.009	0.006	-0.008	0.021
married	0.100	-0.149	0.349	0.290	-0.251	0.831
higher educ.	-0.158	-0.375	0.059	0.127	-0.353	0.607
unemployed	**-0.639*** **	-1.106	-0.172	-0.226	-1.242	0.790
air pollution (p)				-0.060	-0.339	0.220
noise pollution (p)				-0.231*	-0.464	0.001
water pollution (p)				0.267*	-0.032	0.566
litter pollution (p)				0.113	-0.137	0.363
hazard (p)				0.052	-0.240	0.343
greenspace (p)				0.193	-0.204	0.590
green walk (p)				0.319*	-0.031	0.669
green bike tracks (p)				0.118	-0.119	0.356
nature reserve (p)				0.053	-0.246	0.351
scenery(p)				**0.408** **	0.100	0.716
outdoor_score				**0.084*** **	0.053	0.114

level of significance: *** p<0.01 ** p<0.05 * p<0.1. (p) indicates perceived characteristics

[a] AIC cannot be determined with a two-stage LS regression.

5.4.5 Do perceived climate attributes climate match objective climate indicators?

To assess how well perceived climate attributes matched objective climate indicators, I first estimate correlations between the two types of measures. I then build predictive regression models for each specific perceived climate characteristics.

5.4.5.1 Pairwise correlations

Pearson R correlation coefficients are estimated for the whole sample as well as across the temperate and the warm zones.[70] The correlation between perceived cold and actual cold temperature indicators is relatively strong in regions where temperatures in winter are mild but is very weak in the temperate zone where cold temperatures occur frequently: it is possible that colder temperatures in the temperate zone are perceived differently depending on personal characteristics (Lindner-Cendrowska & Blazejczyk, 2018). The correlation between perceived hot and actual hot temperature indicators is relatively strong across all climate regions. The perception that it is often sunny correlates strongly with actual sunny conditions, but less so in tropical/ sub-tropical regions where solar radiation tends to be higher for the same sunshine duration (Bureau of Meteorology, 2022). Perception of a rainy climate is moderately associated with the *frequency* of rain. Perception of windiness is slightly stronger for the temperate zone, possibly because of the windchill factor.

5.4.5.2 Predictive regression models for perceived climate attributes

Regression models are estimated to predict the following perceived climate characteristics: 'perceived cold', 'perceived hot', 'perceived raininess 'perceived sunniness' and 'perceived windiness' (Model 5). Based on empirical evidence, that weather conditions on the day of survey may influence satisfaction ratings (Section 5.2.3), I include a variable representing the value of the specific climate attribute on the day of survey. As previous research indicates that housing thermal attributes (insulation etc.) are important determinants of thermal comfort (Parsons, 1993, 2020), I also incorporate perceived thermal attributes of the home as predictors for temperature perception (Table 5-5).

[70] All pairwise correlation coefficients are shown in Table 5-12, Appendix E.

Table 5-5: Results for Model 5: determinants of climate perceptions

DV	**perceived cold**	**perceived hot**	**perceived raininess**	**perceived sunniness**	**Perceived windiness**
Adjusted R^2	0.295	0.114	0.044	0.234	0.117
AIC	883.2	934.3	791.5	750.1	900.0
n	287	287	286	286	287
variables	Coeff/ CI	Coeff/ CI	Coeff/CI	Coeff/CI	Coeff/CI
temp on day	**-0.036****	0.005			
	-0.069 -0.003	-0.029 0.038			
temp coldest	**-0.092*****				
	-0.129 -0.055				
house cold	**0.554*****				
	0.252 0.856				
days> 30°C		**0.007*****			
		0.004 0.011			
house hot		0.214			
		-0.106 0.534			
rain on day			-0.117		
			-0.392 0.157		
no. rainy days			**0.010*****		
			0.005 0.016		
tropical			-0.174	0.129	
			-0.400 0.052	-0.154 0.413	
sunny on day				0.004	
				-0.011 0.020	
solar radiation				**0.201*****	
				0.141 0.260	
wind speed					*0.021**
					-0.001 0.043
temperate					**0.810*****
					0.532 1.088

level of significance: *** p<0.01 ** p<0.05 * p<0.1

For each climate characteristics, the relevant objective indicator is a significant predictor of how it is perceived; however, the predictive power of each model measured by the AIC is stronger for perceived sunniness (AIC=750.1) than for perceived hot (AIC=934.3). The proportion of the DV (perception) variation explained by each model, measured by the adjusted R^2, is relatively weak, ranging from adjusted R^2=0.044 for raininess to adjusted R^2=0.295 for perceived cold, which suggests that for some attributes, e.g., raininess and windiness, other factors such as individual characteristics play an important role in how actual conditions are perceived. The weather conditions on the day of survey only impact significantly on the perception that the climate is too cold, otherwise it seems that their incidence on climate perception is not significant. There is a stronger perception that the

climate is cold if the respondent feels that their home gets cold quickly, but housing thermal conditions have no apparent influence on the perception that the climate is too hot.

5.4.6 Association between life satisfaction and perceived and actual local conditions.

Our final two models evaluate the association between climate variables and LS depending on whether these variables are subjective perceptions or objective indicators. In Model 6 LS is regressed against perceived environment and climate characteristics, while in Model 7 I substitute perceived climate characteristics for objective climate indicators. In both models, I control for socio-demographic factors as well as wealth status and health status.

In both models, the proportion of LS variation explained by explanatory factors is moderate with adjusted R^2=0.448 in Model 6 and adjusted R^2=0.422 in Model 7, however the predictive power of Model 6 is stronger (AIC=1,009 vs AIC=1,029) (Table 5-6). Self-assessed health and self-assessed wealth remain strong predictors with very similar coefficients as in Model 2. Perceived climate characteristics have a stronger association with LS than actual climate indicators. The perception that it is too hot is a strong negative contributor to LS; while the perception that it is too cold is also a negative contributor, its significance and power are not as strong. In contrast, neither matching of the objective indicators representing hot and cold temperatures have a significant influence on LS. Weather conditions on the day of survey (temperature, rain, and solar radiation) had no impact on LS ratings. Among perceived environment characteristics, the perceived presence of beautiful scenery in the local area was the only significant positive factor to influence LS. Control variables behave similarly in both models (and in Model 2) with age (squared) being the only significant positive contributor.

A test for robustness model (Model 8) including only objective climate variables and objective socio-economic variables was estimated to confirm the robustness of Model 7. In this model wealth satisfaction was replaced by household income and self-assessed health by the variable ‘having no long term health condition’. Compared to Model 7, the results (not shown) indicate that the test model had a slightly better predictive power (AIC =977 vs AIC = 1,029), but the proportion of LS variations explained by explanatory factors was lower (R^2= 0.338 vs R^2 = 0.422). Health condition, household income and age remain strong predictors of LS. As in Model 7, none of the objective climate variables had a statistically significant impact.

Table 5-6: Results for Models 6 and 7: impact of climate and environment characteristics on LS

	Model 6			Model 7		
DV	**LS**			**LS**		
Adjusted R^2	0.450			0.423		
AIC	1009.4			1029.7		
n	260			261		
variables	**Coeff**	**CI**		**Coeff**	**CI**	
wealth (self-assessed)	**0.667*** **	0.378	0.955	**0.660*** **	0.361	0.960
health (self-assessed)	**0.698*** **	0.479	0.917	**0.694*** **	0.468	0.919
too_cold (p)	*-0.161**	-0.341	0.020			
too_hot (p)	**-0.213** **	-0.387	-0.039			
rainy (p)	-0.060	-0.298	0.178			
sunny (p)	0.039	-0.194	0.272			
windy (p)	-0.131	-0.321	0.059			
air pollution (p)	-0.104	-0.353	0.145	-0.108	-0.367	0.151
noise pollution (p)	-0.038	-0.241	0.165	-0.126	-0.333	0.080
water pollution (p)	-0.105	-0.370	0.160	-0.161	-0.435	0.113
litter pollution (p)	-0.092	-0.310	0.125	-0.052	-0.277	0.172
envir. Hazard (p)	-0.041	-0.292	0.209	0.003	-0.249	0.255
greenspace(p)	0.156	-0.188	0.500	0.183	-0.169	0.535
green walk(p)	0.041	-0.271	0.354	0.053	-0.270	0.375
green bike track (p)	0.099	-0.113	0.312	0.101	-0.116	0.318
nature area (p)	-0.136	-0.406	0.133	-0.117	-0.388	0.154
scenery (p)	**0.304** **	0.033	0.576	**0.318** **	0.035	0.600
outdoor_score	0.002	-0.026	0.030	0.002	-0.027	0.031
female	-0.361	-0.804	0.030	-0.257	-0.711	0.197
age (square)	**0.020*** **	0.007	0.082	**0.022*** **	0.009	0.035
married	0.205	-0.269	0.032	0.231	-0.262	0.724
higher ed.	-0.165	-0.577	0.679	-0.200	-0.627	0.226
unemployed	-0.494	-1.441	0.247	-0.545	-1.522	0.432
temp on day				0.014	-0.043	0.071
rain on day				-0.178	-0.703	0.348
sunny on day				-0.013	-0.046	0.020
temp coldest				-0.012	-0.131	0.106
days > 30°C				0.000	-0.007	0.006
no rainy days				-0.005	-0.018	0.009
solar radiation				0.059	-0.152	0.270
wind max speed				-0.021	-0.056	0.013
house cold				-0.316	-0.839	0.206
house hot				0.213	-0.312	0.737
tropical climate				0.221	-0.499	0.941

level of significance: *** p<0.01 ** p<0.05 * p<0.1. (p) indicates perceived characteristics

5.5 Discussion

In this section, I discuss the results from the model estimation presented previously. While interpreting the results, it is important to bear in mind that the study is a preliminary exploratory study with several limitations that are discussed in more details in the conclusion section (Section 5.6.2). The results from Model 2 show that satisfaction with the local climate and satisfaction with the local environment contribute positively to individual LS when controlling for socio-demographic factors, self-rated wealth status and health status. These contributors together explain almost 50% of the variations in LS and climate satisfaction ranks almost equally with self-rated health status and wealth status as a LS contributor. The fact that satisfaction with the local climate contributes significantly to LS is an important finding as to my knowledge, this association has never been investigated before. Thus, the findings of this preliminary study support the relationship between climate satisfaction and LS (RQ_1), and environment satisfaction and LS (RQ_2) within the conceptual model (Fig 5-1).

Results suggest that the impact of environment satisfaction on LS is somewhat weaker than the impact of climate satisfaction; however, it is important to note that the two variables are measured very differently: climate satisfaction is measured as a subjective cognitive evaluation on a five-point Likert scale, while environment satisfaction in this study is measured by a summative value representing the number of perceived wellbeing benefits from the environment. These wellbeing benefits cover a wide scope: physical, mental and spiritual wellbeing, all of which have been shown to be associated with higher SWB (Rieger et al., 2023).

The results from Model 3 indicate that perceived climate conditions influence the cognitive evaluation of the local climate and climate satisfaction. Another important outcome is that perception of a 'healthy climate' is a compounding variable: respondents who believe that the local climate benefits their health are more likely to enjoy the local climate overall. In terms of specific climate characteristics, I find that the perceptions that the climate is 'too hot' or 'too cold' decrease satisfaction with the local climate while perceptions about 'windiness' and 'raininess' have little influence. This is consistent with existing evidence about the influence of the corresponding objective attributes on LS (Maddison & Rehdanz, 2011).

Perceived hot climate appears to be the dominant negative contributor to wellbeing among respondents in the study sample. Previous research that examined the effect of heat on wellbeing in Australia reported little effect from heat stress on either LS or transient

happiness for people with a high level of eudaimonia (sense of purpose) (Zander et al., 2019). Conversely, perceived high temperatures were found to be an important reason behind the decision to leave a tropical city that regularly experiences hot conditions (Zander & Garnett, 2020). Perceived cold does not seem to have a strong influence on climate satisfaction in the study sample. Unlike hot temperatures that are felt in all climate zones in Australia, cold is only experienced relatively briefly and in specific regions such as Tasmania. The same model estimated with data sampled from a country with a much colder climate (for example New Zealand) might deliver a different pattern of relationships. The perception of sunniness is the most important positive factor associated with both perceived climate health benefits and climate satisfaction. While the positive impact of sunny *weather* conditions on LS ratings has been documented in previous research (Barrington-Leigh, 2008; Feddersen et al., 2016), the impact of a sunny *climate* has barely been mentioned.[71] Thus, the findings from this preliminary study support the relationship between perceived climate attributes and climate satisfaction (RQ_3) within the conceptual model.

Results from Model 4 suggest that natural environment attributes influence the level of satisfaction with the local environment. The positive impact of environment amenities, specifically the nearby presence of beautiful scenery is stronger than the negative impact of environmental ills. Two findings stand out: frequent outdoor activity is associated with a high level of environment satisfaction and females tend to be more satisfied with the local environment. It is worth noting that the environmental attributes identified in this study reflect subjective perception by respondents, not objective environmental indicators. Previous evidence suggests that self-reported environmental attributes may be more closely associated with wellbeing than physical reality (Hur et al., 2010), however discrepancies between subjective perceptions and objective indicators have also been reported in the literature (Kothencz & Blaschke, 2017; Ma et al., 2018). The weak or non-significant impact of environmental pollution can be explained by the low level of perceived pollution and the relatively pristine environment in the areas covered by this study compared to Europe where previous research on this topic has been conducted (Luechinger, 2009; MacKerron &

[71]In their Ireland study Brereton et al. (2008) found that sunshine hours were actually negatively correlated to LS. However, they note that this surprising result might be driven by the fact the regions with higher rainfall and less sunshine happen to be scenic regions in the west of the country.

Mourato, 2009). Thus, the findings support the existence of a relationship between perceived environment attribute and satisfaction with the local environment (RQ_4) within the conceptual model.

Results from the successive estimations of Model 5 indicate a relatively good level of consistency between subjective perception of climate attributes and actual indicators; however, the low predictive power for some models suggests the likely presence of omitted variables. Pairwise correlations show that the association between perception and reality is particularly strong for the perception of cold temperature and the perception of a 'sunniness' and to a lesser extent for the perception of hot temperatures.

Respondents are more likely to describe the climate as 'too cold' if the survey took place on a cold day, however there is no evidence that a hot day or a sunny day will influence the opinion that the climate is generally hot or sunny. Likewise the influence of current weather conditions on LS ratings noted in some previous research (Connolly, 2013; Feddersen et al., 2016) was not confirmed by this study. Somewhat surprisingly in a country more accustomed to hot temperatures than cold temperatures, living in what is perceived as a 'cold' home contributes to the feeling that the climate is too cold, but living in a house that gets hot quickly has no impact on the perception that the climate is too hot. Thus, the finding from this preliminary study support the existence of an association between actual climate observations and perception of these attributes (RQ_5) within the conceptual model.

The comparison of results from Model 6 and 7 suggests that perceived climate characteristics are more strongly associated with overall LS than objective climate observations (RQ_6 in the conceptual model). For example, perceived hot climate is significantly and negatively associated with LS in Model 6, but the coefficient for the matching objective indicator (number of days over 30°C) is not significant in Model 7. The same observation applies to a lesser extent to perceived cold. This outcome aligns with previous evidence from the LS research literature that subjective variables are generally stronger predictors of LS ratings than objective factors (Ettema & Schekkerman, 2016; Kubiszewski et al., 2018; Q. Li et al., 2018). The results for robustness test model (Model 8) suggests that self-assessed health and wealth satisfaction are good substitutes for the corresponding objective variables.

The results from Model 6 also indicate that when LS is regressed against perceived climate characteristics and perceived environment characteristics the predictive power is

almost identical to that of Model 2 where LS is regressed against climate satisfaction and environment satisfaction. This suggests that these cognitive evaluation variables are good substitutes for perceived characteristics about the local area as determinants of LS.

5.6 Conclusion

5.6.1 Summary and implications of findings

The purpose of this chapter was to examine the process through which local climate and environmental factors influence individual LS using a conceptual framework supported by a multistage analysis. To my knowledge, this preliminary study is the first that seeks to investigate the association between actual and perceived climate factors, it is also the first to measure the level of satisfaction with the local climate and the local environment and to examine the contribution of these variables to overall SWB. The study also contributes to the limited research that has so far examined the concurrent impact of environmental and climate factors on LS.

This general inquiry is exploratory in nature and is structured around six separate research questions. The outcomes from the investigation are as follows. A positive subjective evaluation of the local climate is associated with higher LS scores (RQ_1); similarly, a high level of satisfaction with the natural environment is associated with increased LS (RQ_2). There is relatively strong evidence that perceived climate characteristics impact overall climate satisfaction (RQ_3); this influence seems to be compounded by the perception that the local climate is beneficial for one's physical and mental health. The perception of health and wellbeing benefits is used as a proxy of the level of satisfaction with the natural environment. The analysis provides a moderate level of evidence that perceived environmental amenities are associated with a higher level of satisfaction with the natural environment; this relationship is reinforced by a high frequency of outdoor activity *(RQ_4)*. The analysis provides weak evidence supporting that subjective perceptions match objective climate attribute (RQ_5). The level of association between the subjective and objective factors will depend on the type of attributes and the climate zone where the individual resides. Lastly, the findings from this preliminary study confirm that as for many other contributing factors (environment, income, neighbourhood characteristics) perception about climate attributes has a stronger influence on LS than actual observations (RQ_6).

The first implication of these findings is that satisfaction with the local climate seems to matter almost as much to SWB as satisfaction about wealth and health, and that the perception that the local environment benefits physical, mental, and spiritual wellbeing is also

an important contributor. The second implication is that in Australia, the perception that the climate is too hot has a strong negative influence on both climate satisfaction and LS while a perception that the climate is too cold has a significant but more limited role. In view of this outcome, the anticipated rise in local temperatures due to climate change (IPCC, 2022) is likely to be felt through complex interactions of negative (less feeling of cold) and positive feedback loops (increased feeling of hot). The third implication is that a positive evaluation of the local climate and the local environment is impacted by the perception that they have a beneficial impact on physical, mental health or spirituality. The number and frequency of outdoor activities is also an important compounding factor in that perception: it seems that people who exercise outdoor on a regular basis are more aware of the local climate and enjoy the natural environment. The overall benefit from outdoor activities appears therefore twofold: health benefits from exercise and perceived wellbeing benefits from the natural environment and the climate.

5.6.2 Limitations

This preliminary study has several limitations that may impact the replication and generalisation of the results. A first limitation is the size of the sample (around 300 observations). Prospective power testing was not possible, given that the exploratory nature of the research would not allow to determine a hypothetical effect size and standard deviation. Post-hoc power testing is arguably meaningless in this instance as no inference could be made from the determined post-hoc power that would be in effect the observed p-value (Dziak et al., 2020). Therefore, confidence intervals have been reported given that this is considered the best practice in these situations.

A second limitation is the low response rate that could impair the representativity of our sample: for instance, the fact that individuals in our sample are older and more highly educated may impact the generalisation of our findings given that these two variables are known to impact LS. It is also possible that respondents to this survey were predominantly people who had a higher awareness of local climatic and environmental conditions, while people who pay little attention to their surrounding conditions chose not to respond. The low response rate for the WA sub-sample (with a high percentage of residents living in an urban area) supports this assumption. While the analysis certainly calls for replication using a larger sample, the results from this exploratory study provide some pertinent insights into how climate factors influence LS and opens avenues for future confirmatory research.

A final limitation lies with the subjective evaluation of climate and environmental factors by respondents. It can be argued that this evaluation may vary over time and therefore it should be captured at various points in time. There is also a possibility that recent weather conditions may influence the perception of specific climate attributes and the overall evaluation of the local climate. These problems could arguably be addressed through the use of a larger sample of data as individual biases would then be averaged.

5.6.3 Practical implications

Notwithstanding the above qualifications, this research significantly contributes to the empirical literature on wellbeing by providing further insight into the influence of local climate factors on SWB and highlighting the contrast between subjective perception and objective climate factors. It confirms that people who live in an area with a pleasant climate and an enjoyable environment are likely to feel happier and less likely to move somewhere else (Rappaport, 2007). The findings from this research, when confirmed by a larger study have potential policy implications. Firstly, in a world where the climate is getting hotter, possible strategies of adaptation could be articulated emphasising the positive impact of a sunnier climate and the promotion of climate health benefits. Secondly, the findings may inform, and guide initiatives aimed at improving perception of and adaptation to the specific attributes of the local climate; for instance, in a tropical climate, outdoor activities such as hiking, cycling, and gardening could be encouraged during the dry season when temperatures are moderate and humidity levels relatively low. Thirdly, the findings provide support for promoting the enjoyment of local natural environment amenities while adapting to the local climate conditions: for instance, appreciating the rainforest at different seasons.

5.7 Appendix to Chapter 5

5.7.1 Appendix A: Sample frame selection for mailout survey

Table 5-7: Queensland mailout participant selection

Agro-ecological region	LGA/ Statistical areas	Approximate Post codes	List	Final sample	Ratio
Darling Downs	Toowoomba	7350	10,468	250	1 out 42
	Dalby- Oakey, Milmeran, Toowomba surrounds	4352-4365; 4400-4408	8,916	250	1 out 35
Wide Bay Burnett	Noosa- Gympie	4563-4601	8,206	100	1 out 82
	Maryborough- Fraser Coast	4650-4659	11,887	125	1 out 95
	Biggenden Monto	4620-4630	1,559	50	1 out 31
	Bundaberg Region	4660-4677	11,965	125	1 out 95
	Gladstone Region	4680-4694-4695	5,498	100	1 out 55
Burdekin	Townsville	4810-4818 (except 4816)	18,537	250	1 out 74
	Charters Towers/ Townsville country	4805-4809;4816; 4820	6,390	250	1 out 26
Wet Tropic Coast	Cairns	4865-4870;4878-4879	16,557	250	1 out 66
	Douglas	4873; 4877; 4881	2,052	50	1 out 41
	Cassowary Coast/ Hinchinbrook	4849;4850; 4851-4864;4871	7,143	200	1 out 36
TOTAL				**2000**	

Table 5-8: Tasmania mailout participant selection

Agro-ecological region	Localities	Approximate Post codes	List	Final sample	Ratio
Hobart	Greater Hobart	7000-7024	17,509	200	1 out of 87
	Hobart surroundings: Huon Valley. Channel, New Norfolk	7050-7055;7109-7117; 7140 7155-7163	7,912	150	1 out 53
North Central	Greater Launceston	7248-7250	9,540	200	1 out 48
	Meander- Tamar- Scottsdale-North Midland	7252-7254 7258-7304	7,318	150	1 out 49
Burnie	Burnie-Devonport- Penguin-Ulverstone-Kentish_Wynyard	7305;7306;7307;7310;7315;7316;7320;7322;7325	15,111	300	1 out 50
TOTAL				**1,000**	

5.7.2 Appendix B: Response rates

Table 5-9: Email survey response rates

	Queensland	**Tasmania/ Victoria**	**Western Australia**	**TOTAL**
Total emails sent:				
1st wave:	3,596	3,609	6,936	14,141
2nd wave:	3,576	3,241	6,779	13,596
TOTAL: (A)	7,172	6,850	13,715	27,737
Less non-delivered (B)	(419)	(338)	(1,339)	(2,096)
= Gross sample (C = A-B)	6,753	6,572	12,376	25,641
Responses received (D)	107	88	87	282
Less non-usable responses (E)	(16)	(15)	(33)	(64)
Usable responses F = (D-E)	**91**	**73**	**54**	**218**
Response rate (G = F/C)	***1.34%***	***1.11%***	***0.50%***	***0.85%***

Table 5-10: Mailout survey response rates

	Queensland	**Tasmania**	**TOTAL**
Total post cards sent:			
1st wave:	1,000	500	1,500
2nd wave:	1,000	500	1,500
TOTAL: (A)	2,000	1,000	3,000
Responses received (B)	58	30	88
Less non-usable responses (C)	(8)	(3)	(11)
Usable responses (D = B-C)	**50**	**27**	**77**
Response rate (E= D/A)	***2.5%***	***2.7%***	***2.56%***

5.7.3 Appendix C: Response bias testing

Two key screening questions were used for the purpose of the non-bias tests:

Q7) All things considered, how satisfied are you with your life overall?
*Q19) What **best** describes how you feel about the climate in the area where you live?*

I test the null hypothesis *(H_0)* that the values representing the answers to the screening questions are independent of the fact that the respondent was contacted through one mode or the other. Test results are interpreted based on the p value associated with the test for equality of variances (Levene's Test). If $p < 0.05$, then H_0 is rejected, and it is inferred that the responses are dependent on the group of the respondent. As both responses can be measured on an ordinal scale, a parametric test (independent samples t- test) can be used. The p-value returned for both questions ($p=0.743$ and $p=0.679$) are both well above the significance

threshold indicating that the null hypothesis cannot be rejected and therefore the answers are presumed independent of the mode of contact.

5.7.4 Appendix D: Variables used for this study.

Table 5-11: Variables used for survey data other than climate observations

Category	Variable name	Measurement
Subjective wellbeing	Overall life satisfaction (LS)	Likert scale 0-10
Personal characteristics	Age	age squared
	Gender	Dummy (female)
	Education status: highest qualification	Dummy (university qual.)
	Marital status	Dummy (married/ de facto)
	Employment status	Dummy (unemployed)
Determinant of LS	Self-rated wealth income status	Likert scale; 1-5
	Self-rated health status	Likert scale: 1-5
	Satisfaction with climate	Rated on a 1 to 6 scale
	Satisfaction with environment (Wellbeing benefits)	Number of identified benefits (max 7)
Determinants of climate satisfaction	Climate perception: 'too cold', 'too hot' rainy, windy, sunny	Rated on a 1 to 5 scale
	Health benefits from climate: physical & mental	Rated on a 1 to 5 scale
	Outdoor activities	Frequency rated on a 0-5 scale for each activity total 12 activities
Determinant of environment satisfaction	Wellbeing benefits: physical, mental, spiritual	Dummy for each benefit
	Self-reported environmental 'ills': pollution	Rated on 1to 5 scale
	Self-reported environmental amenities: greenspace, walking, biking, nature, scenery	Rated on 1 to 5 scale
	Outdoor activities	see above
Determinant of climate perception	Relevant actual climate observations for following perceptions: 'too cold' 'too hot' rainy windy sunny	See Table 2-8 Chapter 2
	Weather conditions on day of survey: temperature rain, solar radiation	See Table 2-8 Chapter 2
	Home thermal attributes: gets cold quickly	Rated on a 1 to 5 scale
	Home thermal attributes: gets hot quickly	Rated on a 1 to 5 scale

5.7.5 Appendix E: Climate observations and climate perception

Table 5-12: Pairwise correlations (Pearson R) between actual climate variables and perception

Climate variable	Whole sample	Temperate	Warm
n	287	111	176
'It is too cold in Winter"			
Average minimum temperature	-0.517***	-0.096	-0.383***
Minimum temperature coldest month	-0.492***	-0.049	-0.352***
Mean temperature coldest month	-0.498***	-0.038	-0.360***
Number of days temperature < 5 ° C	0.373***	0.040	0.332***
Heating Degree Months	0.477***	0.031	0.367***
"It is too hot in Summer"			
Average maximum temperature	0.321***	0.213**	0.150**
Maximum temperature hottest month	0.336***	0.302***	0.151**
Mean temperature hottest month	0.331***	0.248***	0.158**
Number of days temperature > 30 ° C	0.342***	0.348***	0.214***
Cooling Degree Months	0.306***	0.208**	0.178**
"It rains too much too often"			
Average annual rainfall	0.086	0.193**	0.190**
No of rainy days per year	0.208***	0.286***	0.182**
Rainfall in wettest month	0.025	0.107	0.146
No Months with rainfall >= 100 mm	-0.008	0.062	0.136
"It is often too windy"			
Average maximum daily wind speed	0.152**	0.212**	0.010
"It is often sunny"			
Average daily solar exposure	0.488***	0.270***	0.170**

Statistical significance: ** p, 0.05, *** p <0.01

Chapter 6 How selective mobility, social and ecological influence may impact geographic variations in life satisfaction scores: an Australian longitudinal study.

In this chapter, I address Research Objective #4 identified in Chapter 1 and explore how spatial clustering of LS scores could develop in association with selective mobility, social influence, or ecological influence, while controlling for personality traits and socio-demographic characteristics. To my knowledge, this is the first study that investigates the association between LS levels and selective mobility. It is also the first time that a longitudinal study is used to examine the potential influence of the geographic location of the residence on individual LS levels. The analysis reveals that LS level prior to the move may impact choice of specific type of mobility such as moving to the country or moving to a region with a different climate. It also suggests that individual LS trajectory over time may be influenced by a different social and ecological environment after the move.

This chapter is based on an article published in *Social Indicators Research* in June 2024. The citation for this article is as follows:

Lignier P., Jarvis D., Grainger D., Chaiechi T., 2024, 'How selective mobility, social and ecological influence may impact geographic variations in life satisfaction scores: An Australian longitudinal study' *Social Indicators Research*, https://doi.org/10.1007/s11205-024-03373-0 [72]

The article was edited for inclusion in this thesis to remove information already discussed elsewhere. Footnotes indicate where notable amendments have been made to the original manuscript. Minor amendments have also been made to ensure consistent use of terminology within this thesis.

Abstract:

The spatial clustering of life satisfaction scores noted in recent empirical research suggests that "happier" people may live in specific neighbourhoods or regions. This prompts

[72] Individual authors' contributions: P Lignier, conceptualisation, design, data analysis and manuscript writing; D Jarvis, project supervision, conceptual guidance and critical manuscript review; D Grainger: project supervision, technical guidance and critical manuscript review; T Chaiechi, project supervision and critical manuscript review

the questions: Do “happier” people choose to move to specific places? Does living in specific places make people “happier”? To answer these questions, this chapter explores possible occurrences of selective mobility, and social and ecological influence. Using panel data collected in Australia from 2013 to 2021, I examine the association between life satisfaction scores and selective geographic mobility, and the possible influence that living at specific locations may have on individual life satisfaction trajectory, while controlling for individual personality traits and socio-demographic factors. The results indicate that urban residents reporting lower life satisfaction scores before the move have a higher probability of moving to a rural area. Similarly, lower life satisfaction scores are associated with a higher probability of moving to a region with a different climate. I also find evidence that moving from the city to the country is associated with an uplift of the life satisfaction trajectory for the individual. A similar conclusion is reached for people who moved to a warmer climate, but *not* for a move to a cooler climate. To my knowledge, this is the first time the concepts of selective mobility and social and ecological influence have been applied in life satisfaction research. This work provides an indicator that could be important to demographers predicting population movements. It can also inform policy development around assisting regional and rural areas attract/ retain residents to support regional sustainability.

6.1 Introduction[73]

Spatial clustering of life satisfaction (LS) self-rated scores has been documented in several recent intra-country studies (Helliwell et al., 2019; Jokela et al., 2015; Kubiszewski, Jarvis, et al., 2019; Oswald & Wu, 2011); however little research has been devoted so far to investigating the possible reasons why this is happening.[74] Research examining spatial variations in psychological traits has posited that three of the mechanisms explaining spatial clustering are selective residential mobility, social influence and ecological influence (Rentfrow & Jokela, 2016).[75] In this chapter, I am exploring whether wellbeing and personality traits together can act as an indicator of mobility, informing policy development

[73] Significant content in this section has been removed from the submitted manuscript to avoid redundancy of information already included elsewhere in the thesis.

[74] The relevance of geography in LS research was discussed comprehensively in Chapter 2, Section 2.3.3.1.

[75]The concepts of selective mobility, social influence and ecological influence were discussed in Chapter 1, Section 1.3.7

around attracting/retaining residents into the future to promote sustainability of rural and urban locations in different climates.

The effects of social and ecological influence on personality traits have been examined by several authors (for instance Jokela (2020)); the influence of the social and ecological environment on wellbeing has also been investigated to some extent, in particular the impact of rural compared to urban residence on LS and hedonic wellbeing (Gilbert et al., 2016; Weckroth et al., 2022); however the effect of residing in a specific type of climate on both wellbeing and personality has barely been considered. The association between personality traits and selective mobility has received some attention (Campbell, 2019; Jokela, 2020; Jokela et al., 2008). While the relationship between happiness /wellbeing and migration has been examined, the focus has mostly been on international migration (Hendriks & Bartram, 2018; Polgreen & Simpson, 2011); the association between LS and internal migration, particularly in advanced economies has received more limited attention.

Using longitudinal data, this study explores how spatial clustering in LS scores could develop due to selective mobility, social and ecological influence while controlling for personality traits and individual socio-demographic characteristics. As a first step in this investigation, I examine the association between LS and two specific types of selective geographic mobility: moving from the city to a rural area (and vice versa) and mobility to a region with a different climate. The second step considers the social and ecological influence of the type of residence (rural or urban and climate zone) on the within-individual LS trajectory over time.

I derive several research questions that reflect each of the two steps described above. Step one: How does LS score prior to the move impact on a decision to move from the city to the country? from the country to the city? *(RQ_1)* How does LS score prior to the move impact on a decision to move to a region with a different climate? *(RQ_2)* Step two: How does moving to a different type of residence (urban/ rural) affect within-individual LS trajectory over time? *(RQ_3)* How does moving to a different climate zone affect within- individual LS trajectory over time? *(RQ_4).*

The remainder of this chapter is organised as follows. In section 6.2, I briefly review the relevant literature and in section 6.3 I describe the data and the methodology; results are presented in Section 6.4 followed by a discussion in Section 6.5. Finally in Section 6.6, I

summarise the findings from this study, and explain why the research is important and how it can help improve wellbeing by informing policy.

6.2 Literature review

6.2.1 Spatial variations and geographical clustering

Geographical psychology is a discipline that analyses the spatial distribution of psychological phenomena and their relationship with contextual features of the macro-environment (Rentfrow & Jokela, 2016). Geographical psychology has been applied to study the variations in personality, wellbeing, religiosity and other psychological characteristics across nations (Inglehardt & Klingemann, 2000; Lynn & Steel, 2006), across regions within the same country (Rentfrow et al., 2013; Rentfrow et al., 2015; Rentfrow et al., 2009) and within a large metropolitan area (Jokela et al., 2015).

There is some evidence of spatial heterogeneity and clustering in LS levels in Australia with the average score per SA2 varying from around 3 to almost 10 on a 0 to 10 scale, however no discernible geographic pattern emerges (Kubiszewski, Jarvis, et al., 2019; Lignier et al., 2023).[76] A similar finding is reported by researchers in Canada where the difference in mean LS between the bottom and top quintile was found to be significant.[77](Helliwell et al., 2019). In research conducted in the US, Oswald and Wu (2011) note that the differences in wellbeing across states in the US correspond up to 0.2 satisfaction point similar in size to the effect of unemployment or divorce.

6.2.2 Residential mobility, life satisfaction and personality traits

Neo-classical economists traditionally view migration as an investment where the returns will be in the form of maximisation of the migrants' utility function (Sjaastad, 1962; Tiebout, 1956). This paradigm relies on a number of assumptions such as availability of information about the destination location and rationality of the moving decision, that have been challenged by both empirical evidence (Massey et al., 1993; Schkade & Kahneman, 1998) and theory (Lee, 1966). It seems that most people migrate for a variety of reasons, but they expect that this will result in an increased wellbeing and quality of life (Graham & Nikolova, 2015). The analysis is further complicated by the fact that moving generally involves a family unit (Mincer, 1978) and the move may not be beneficial for every members

[76] Spatial diversity of LS scores within Australia was discussed comprehensively in Chapter 2, Section 2.5.2

[77] When normalised to the average standard deviation, the mean for the bottom and the top quintile deviated from the overall mean by a value of -1.5 and +1.5 respectively (see Helliwell et al 2019, Fig 5, p 13).

of the family (Castorina & Welters, 2022). It is also important to bear in mind the possibility of reverse causation between migration and happiness: are happier people more inclined to migrate or does migration cause an increase in happiness? (Bartram, 2011).

Dis-satisfaction with one's life has been found to predict migration to a neighbouring country (Silventoinen et al., 2007). While most migration research has focussed on international migration, a few studies have investigated the impact on LS within the context of internal migration. Nowok et al. (2013) investigate whether people who migrate within the UK become happier after the move than they were before. They find that people who migrate are overall less happy than those who do not. The results from that study suggest that migration generally takes place after a period of stress; happiness peaks just after the move, but in the long term it stabilises to the pre-stress long term level (Nowok et al., 2013). Another study investigating wellbeing and inter-state migration in the US finds that a state with higher wellbeing levels among its residents will attract migrants from other states (Hummel, 2016).

Other research has shown that personality traits and personal background can impact the relationship between wellbeing and migration. People who have moved frequently during their childhood tend to have lower levels of LS; however the association is moderated by extraversion: strongly negative for introverts, almost absent for extraverts (Oishi & Tsang, 2022). At an individual level, high residential mobility is associated with lower levels of wellbeing (Oishi & Schimmack, 2010) but at city level, residential mobility is associated with higher levels of wellbeing: i.e., people currently living in cities with high levels of residential mobility report higher levels of LS *on average* than those living in cities where residents are more stable (Oishi et al., 2015).

6.2.3 Selective geographic mobility

The assumption underlying the concept of selective mobility is that people will choose their place of residence based on where their needs are best satisfied (Rentfrow & Jokela, 2016). This may be based on job opportunities, goods and services provided (Sjaastad, 1962; Tiebout, 1956) but also on whether they derive satisfaction from the community (Florida, 2009) and emotional attachment (Florida & Mellander, 2010). Findings from studies undertaken in the US suggest that people may also choose to migrate to places where the weather is "nice" (Rappaport, 2007).

There is scant evidence about the relationship between happiness levels and particular types of geographic mobility. Research in the UK show that migrants who moved a distance of 25-50 km reported the largest increase in happiness after the move, but long distance migrants seemed happier overall than short distance movers despite the fact that a long distance move meant that community and family connections were likely to be disrupted by such a move (Nowok et al., 2013). However, little is known about the association between pre-move happiness levels and specific types of mobility, for instance from a rural area to an urban area or vice versa. There is some evidence that people with certain personality traits, a factor with a strong correlation with happiness levels (Tellegen et al., 1988), tend to move to certain places rather than others.

Research undertaken in Finland found that individuals with high sociability were more likely to leave a rural area or to stay in an urban area (Jokela et al., 2008). Adaptability and cognitive ability were also associated with a higher probability of migration from rural to urban areas in Norway (Butikofer & Peri, 2017). Jokela (2020) found that among Australian rural residents, extraversion, conscientiousness, and openness to experience were positive predictors of moving to an urban area.

6.2.4 Social and ecological influence on wellbeing and personality traits

An analysis of the spatial distribution of personality traits and LS across postal districts in Metropolitan London shows evidence of clustering of high and low values for the five personality traits and LS scores demonstrating that both types of indicators displayed spatial autocorrelation (Jokela et al., 2015). Likewise, analysis of LS scores for adjoining census districts in Canada indicated the possibility of spillover effects between neighbouring areas: LS mean at area level for one community can be a predictor of LS at area level for adjoining communities (Ziogas et al., 2023).

The positive influence on wellbeing of living near greenspace is well documented in the empirical literature (M. White et al., 2013), but there is still much debate as to whether people are happier in rural areas compared to urban areas. Earlier research conducted in the US indicated that rural residents might be happier (R. Fernandez & Kulik, 1981), however this was not confirmed in later European studies (Shucksmith et al., 2009). Gilbert et al. (2016) found that residents living in remote rural areas in Scotland had higher level of LS but there was no difference between urban residents and residents living in inner rural areas. In Australia, Cummins et al. (2003) reported that people living in rural areas were more satisfied with their personal lives. Similarly, a recent Canadian study shows that average LS scores for

rural census districts were significantly higher than for urban districts (Helliwell et al., 2019; Ziogas et al., 2023). Research investigating regional variations in personality show evidence that regions with higher level of agreeableness in both Great Britain and in the US are generally rural regions, while regions with high openness to experience are generally urban and densely populated (Rentfrow et al., 2013; Rentfrow et al., 2015).

While climate variables such as temperature and sunshine have been shown to have an impact on average LS scores (Brereton et al., 2008; Lignier et al., 2023; Maddison & Rehdanz, 2011; Rehdanz & Maddison, 2005), there is no clear evidence of differences in average LS between climate zones. However a recent Australian study shows that climates with hot and dry attributes have a negative impact on LS, while the influence of milder conditions typical of a warm temperate climate is positive (Lignier et al., 2023). There is also some evidence that natural conditions may have an influence on behaviour and personality traits. Van de Vliert (2013) notes that residents of regions with harsh climate conditions and limited natural resources display more collectivistic and communal values compared to regions with a more favourable natural environment. An investigation of regional variations in personality traits in the US and Great Britain reveals that neuroticism is low in warmer regions (Rentfrow et al., 2013; Rentfrow et al., 2015).

In summary a review of the empirical literature reveals unmistakable evidence of spatial clustering for both LS scores and personality traits. However, the evidence regarding the association between LS and certain types of geographic mobility remains limited. Likewise, we know little about the influence of living in specific types of locations on LS over time. This may restrict development of policies to support improved LS and to support sustainability of distinct types of communities that need to attract/retain people to live and work in those locations.

6.3 Methodology

6.3.1 Database

This project analyses data collected by the HILDA surveys over the period 2013-2021. The HILDA questionnaire asks individual respondents to rate their overall LS on a yearly basis and periodically collects data about personality traits (2013, 2017 and 2021 in our sample). Years when data about personality traits are available are considered baseline years in this study. The annual HILDA data files containing all relevant variables were appended into a single panel dataset. To retain as much data as possible while working with balanced datasets, the appended dataset was split into separate sub-sets for the baseline

periods 2013-2016 and 2017-2021. Respondents who did not have observations for all years of either baseline periods were discarded as were respondents where the data about personality traits was missing. The final structure of the panel dataset was as follows:

- A total of 15,507 respondents, corresponding to 120,188 observations;
- 9,813 respondents (63.28%) had data for the full 9-year period;
- 3,401 respondents (21.97%) had data for the 2013-2016 period only;
- 2,293 respondents (14.79%) had data for the 2017-2021 period only.

6.3.2 Variables

Key variables used in this project relate to residential mobility, life satisfaction, personality traits, socio-demographic characteristics, and type of residence. Each variable category is now described in detail.

6.3.2.1 Residential mobility variables

Individual residential mobility is captured in each wave of the HILDA survey through the question *"did you move in the previous 12 months?"* While mobility itself is recorded as an event, *selective* mobility is determined based on transition data: the change in residence of the respondent between two consecutive waves. A move from the city to a rural area or vice versa was identified when the respondent's residence changed from a residence classified as 'urban' to an area classified as 'rural'.[78] Selective mobility between climate zones was identified when the change of residence was to an area classified under a different climate zone.[79] Distinction was made between moving to a warmer climate zone and moving to a cooler climate zone.

Extensive research reported in the migration literature show that the decision unit in regard to a move is the household rather than the individual (Castorina & Welters, 2022; Mincer, 1978). The HILDA dataset is structured around households, this means that even though the unit of observation in our dataset is the individual, moves will involve all members of the same household. There is also evidence that job-related moves are different as they will typically involve an individual who is a lead mover (the person who decides the

[78] The classification was based on Statistical Area Level 1 (SA1) where the respondent resides. See Section 6.3.2.5 below about rural vs urban residence.

[79] The criteria used to identify different climate zones are described in Section 6.3.2.6.

move) and a tied mover (Castorina & Welters, 2022) with possible different happiness outcomes between the two (Nowok et al., 2013).

6.3.2.2 Life satisfaction

Individual LS is captured each year by the HILDA survey. Existing evidence on internal migration suggests that there is often a period of stress before migration, and that there is typically a lag of two to three years between the low point of happiness/LS and the time of migration (Nowok et al., 2013).

6.3.2.3 Personality traits

Personality traits were assessed by the survey using the Saucier & Goldberg Big Five Marker scale with 8 items for extraversion, 7 items for agreeableness, 7 items for emotional stability, 7 items for conscientiousness and 6 items for openness to experience (Costa & McCrae, 1992; Saucier, 1994). All items were assessed on a 1 to 7 scale with 1 representing *"doesn't describe me at all"* to 7 "*describes me very well"* (Melbourne Institute, 2022). Personality scores were standardised for each year of assessment using the mean and standard deviation.

6.3.2.4 Socio-demographic variables

The inclusion of socio-demographic variables believed to influence residential mobility was guided by previous studies that focused on internal migration (Castorina & Welters, 2022; Jokela, 2020; Nowok et al., 2013). The specific variables were age (squared), sex (female), level of education (measured on a 4-point scale), employment status (binary), household income, marital status (binary), having children (binary).

Two additional variables indicated whether the individual had experienced important life events in the year they moved. The inclusion of these variables is justified by the evidence that important life events often precedes the decision to move (Castorina & Welters, 2022; Nowok et al., 2013). Life events were classified as either favourable or adverse; the incidence of either type of event in the previous year being identified by a dummy variable. Favourable life events include getting married, having a baby, work promotion, retirement, and improvement of personal finance. Adverse events include death of a spouse or relative, jail, domestic violence, and illness.

6.3.2.5 Rural vs urban residence

The rural/ urban classification was based on the remoteness index classification of the statistical area (SA1) of residence at the time of survey, as designed by the Australian Bureau

of Statistics (Australian Bureau of Statistics, 2023c). Remoteness is ordered into five categories: 1 'main cities of Australia', 2 'inner regional', 3 'outer regional', 4 'remote' and 5 'very remote'.[80] SA1 of residence is captured by the HILDA survey. As in the Jokela (2020) study, two categories were retained: 'urban' corresponding to category 1 and rural for categories 2-5. Over the timespan of this study, roughly two thirds of respondents resided in an urban area.

6.3.2.6 Climate zones

Definitions of climate zones were based on the Australian climate zone classification published by the Bureau of Meteorology (2006), but with an emphasis on temperature. Thresholds were selected based on existing evidence about thermal comfort and outdoor activities (Chen & Ng, 2012): 20°C for 'cool/ temperate', 25°C for ' temperate/warm', 30°C for ' warm /hot'. Allocation to a specific climate zone was based on the SA2 of residence at the time of survey. Four of the five largest metropolitan areas are in the temperate zone, the fifth one (Brisbane) is in the warm zone. For the social and ecological influence step of the analysis, the cool and temperate zones were merged into a single 'temperate' zone while the warm and hot zones were merged into a single 'warm' zone.[81]

6.3.3 Method of analysis

Given structure of the data over multiple years, panel data analysis was used as a tool of investigation. Panel data logistic regression (*'xtlogit'* function in STATA) was used for selective mobility given the categorical nature of the dependent variable. Linear regression (*'xtreg'* function) was used for the social and ecological influence analysis as the LS dependent variable is assumed to be of a cardinal nature (Kristoffersen, 2010).

6.3.3.1 Selective mobility analysis

This step addresses research questions RQ_1 and RQ_2 listed in the introduction. For each of these questions, I estimate *three* successive models.

80 The 2016 remoteness classification for each Level 1 Statistical area (SA1) used for this study is available from the ABS website:
https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.005July%202016?OpenDocument

81 Only a limited number of HILDA respondents selected for this study resided in the hot zone.

The first model only includes the LS score *lagged one year*[82] as the independent variable.

$$Y_{it} = \begin{cases} 1 \; if \; x_{i(t-1)}\beta_1 + \alpha_i + \; \varepsilon_{it} > 0 \\ 0 \; otherwise \end{cases} \quad (1)$$

where Y_{it} represents the value of the move variable for individual i in year t, $x_{i(t-1)}$ is the LS score of individual i lagged one year, α_i is a time invariant error term for individual i, ε_{it} is the random error term for individual i in year t and net of the time invariant error α_i.

The second model expands (1) by adding the five (standardised) personality variables as independent variables.

$$Y_{it} = \begin{cases} 1 \; if \; x_{i(t-1)}\beta_1 + p'_{it}\beta_2 + \alpha_i + \; \varepsilon_{it} > 0 \\ 0 \; otherwise \end{cases} \quad (2)$$

where p'_{it} is a vector of variables representing personality traits for individual i in year t.

The third model expands (2) by adding the control variables (socio-demographic variables and life events).

$$Y_{it} = \begin{cases} 1 \; if \; x_{i(t-1)}\beta_1 + p'_{it}\beta_2 + d'_{it}\beta_3 + \alpha_i + \; \varepsilon_{it} > 0 \\ 0 \; otherwise \end{cases} \quad (3)$$

Where d'_{it} is a vector of socio-demographic and life event variables for individual i in year t.

The question arises about whether to use random effects or fixed effects estimator for the regression. Random effect (RE) estimator assumes that the random error term is not correlated to regressors, while fixed effect (FE) (within) estimator regresses the demeaned dependent variable on the demeaned independent variables, thereby eliminating the effect of the time invariant factors. Whilst FE is appropriate in certain circumstances, it is unsuitable here as this approach discards information that remains unchanged (fixed) across the study period. In this study it would require discarding all respondents who did not move at all during the reference period. For this reason, I used RE models for the selective mobility analysis.

For the questions relating to selective mobility, I subdivide the dataset to isolate the factors driving the behaviour of each specific sub-group. Thus, only rural residents at the time of the baseline years are considered for the selective mobility to the city, conversely only

[82] A two-year lagged and three-year lagged values of LS were considered for inclusion based on the findings by Nowok et al (2017), however those variables were not found to be significant, so were dropped from the model.

urban residents at the time of the baseline year are considered for the selective mobility to a rural area (RQ_1); Using the same approach, I use the sub-dataset of people who resided in the cool and temperate zones at baseline year for the selective mobility to a warmer climate; and the sub-dataset of people residing in the warm or hot zone at baseline year for the selective mobility to a cooler climate (RQ_2).

6.3.3.2 Social and ecological influence analysis

The research questions addressed in this second step are *RQ_3* and *RQ_4*. For social and ecological influence, yearly LS score is the dependent variable. All models are regressed using a FE (within) estimator as I am considering the influence of factors that change over time as in Jokela (2020). I estimate *three* successive models for each question: the first model incorporates residence type (urban/ rural or climate zone) as the independent variable:

$\widetilde{y_{it}} = \widetilde{r_{it}}\beta_1 + \widetilde{\varepsilon_{it}}$ (4)
with:
$\widetilde{y_{it}} = y_{it} - \overline{y_i} + \overline{y}$; $\widetilde{r_{it}} = r_{it} - \overline{r_i} + \overline{r}$ and $\widetilde{\varepsilon_{it}} = \varepsilon_{it} - \overline{\varepsilon_i} + \overline{\varepsilon}$
where y_{it} is the LS score of individual i in year t, r_{it} is the type of residence of individual i in year t, ε_{it} is the time dependent random error term for individual i in year t.

The second model expands (4) by adding the five standardised personality traits:
$\widetilde{y_{it}} = \widetilde{r_{it}}\beta_1 + \widetilde{p'_{it}}\beta_2 + \widetilde{\varepsilon_{it}}$ (5)
with:
$\widetilde{p'_{it}} = p'_{it} - \overline{p'_i} + \overline{p'}$
where p'_{it} is a vector of variables representing personality traits for individual i in year t.

The third model expands (5) by adding control variables for health status, marriage status and income.
$\widetilde{y_{it}} = \widetilde{r_{it}}\beta_1 + \widetilde{p'_{it}}\beta_2 + \widetilde{d'_{it}}\beta_3 + \widetilde{\varepsilon_{it}}$ (6)
with:
$\widetilde{d'_{it}} = d'_{it} - \overline{d'_i} + \overline{d'}$

6.4 Results

6.4.1 Descriptive statistics

6.4.1.1 Residential mobility

Out of the total 15,507 respondents, 5,158 were rural residents in the baseline year (2013 or 2017) and 10,349 were urban residents. About 50% of all respondents moved at least once during the whole period of study; the proportion is similar among rural and urban residents. 12.1% of rural residents moved to the city and 7.5% of urban residents move to a rural area (Figure 6-1). Overall, 6.1% of respondents moved to a warmer climate zone while 6.2% moved to a cooler zone (Figure 6-2). Among reasons for moving, study and work were

strongly and positively associated with a move from rural to city locations. Moving for work reason was also significantly positively associated with moving to a warmer climate and moving to a rural area The correlation coefficients between moving for lifestyle reasons and any type of selective mobility were very weak (Table 6-1).

Table 6-1: Reasons for moving: partial correlation for each type of move

Reasons for moving	move to city (rural residents)	move to rural (urban residents	move to warmer climate	move to cooler climate
Work	**0.100****	**0.084****	**0.108****	**-0.065****
Study	**0.191****	-0.008	**0.023****	-0.013
Lifestyle	**-0.075****	**-0.041****	**-0.042****	**0.057****
Family	**0.050****	0.008	**0.027****	-0.011
Health	0.017	0.012	**0.033****	-0.005
Neighbourhood	**-0.034****	-0.000	-0.015	0.014

** significant at p<0.05 level

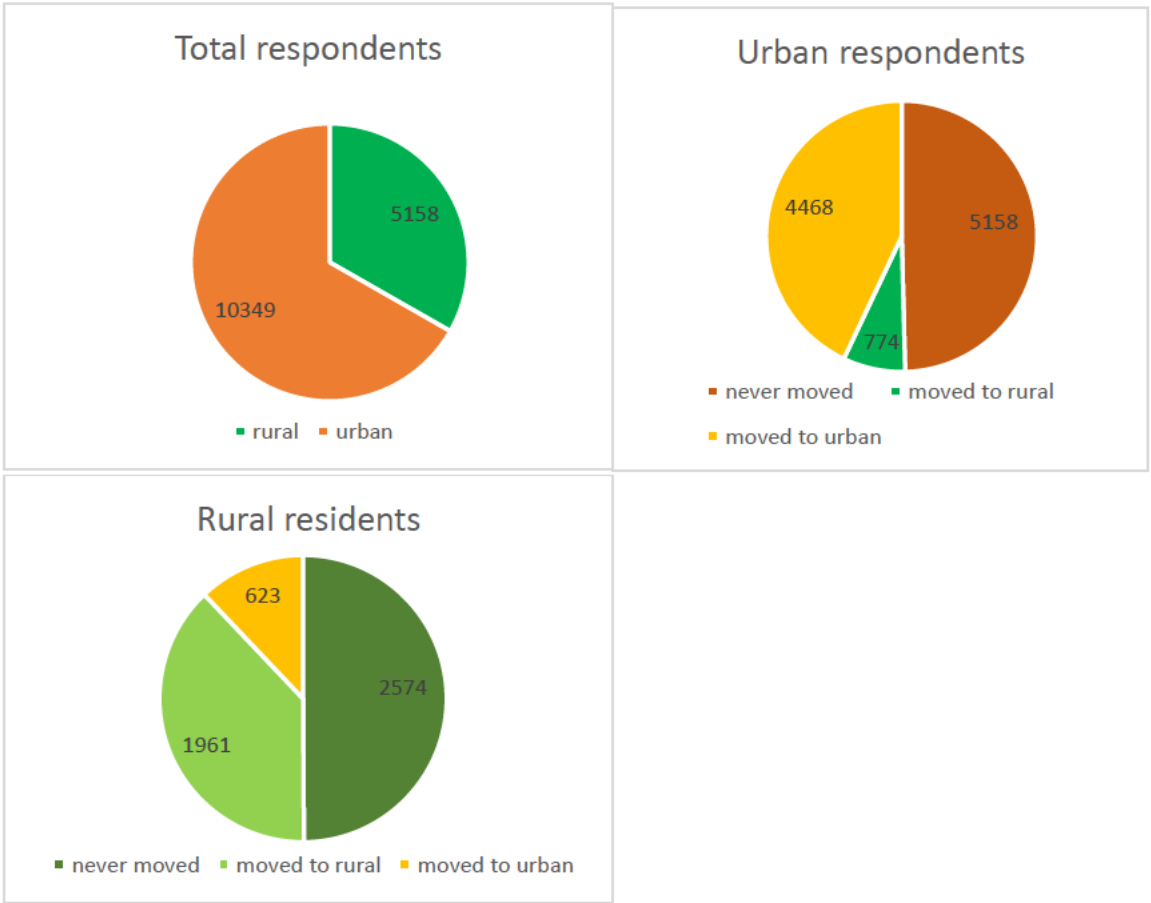

Figure 6-1: Residential mobility: urban vs rural

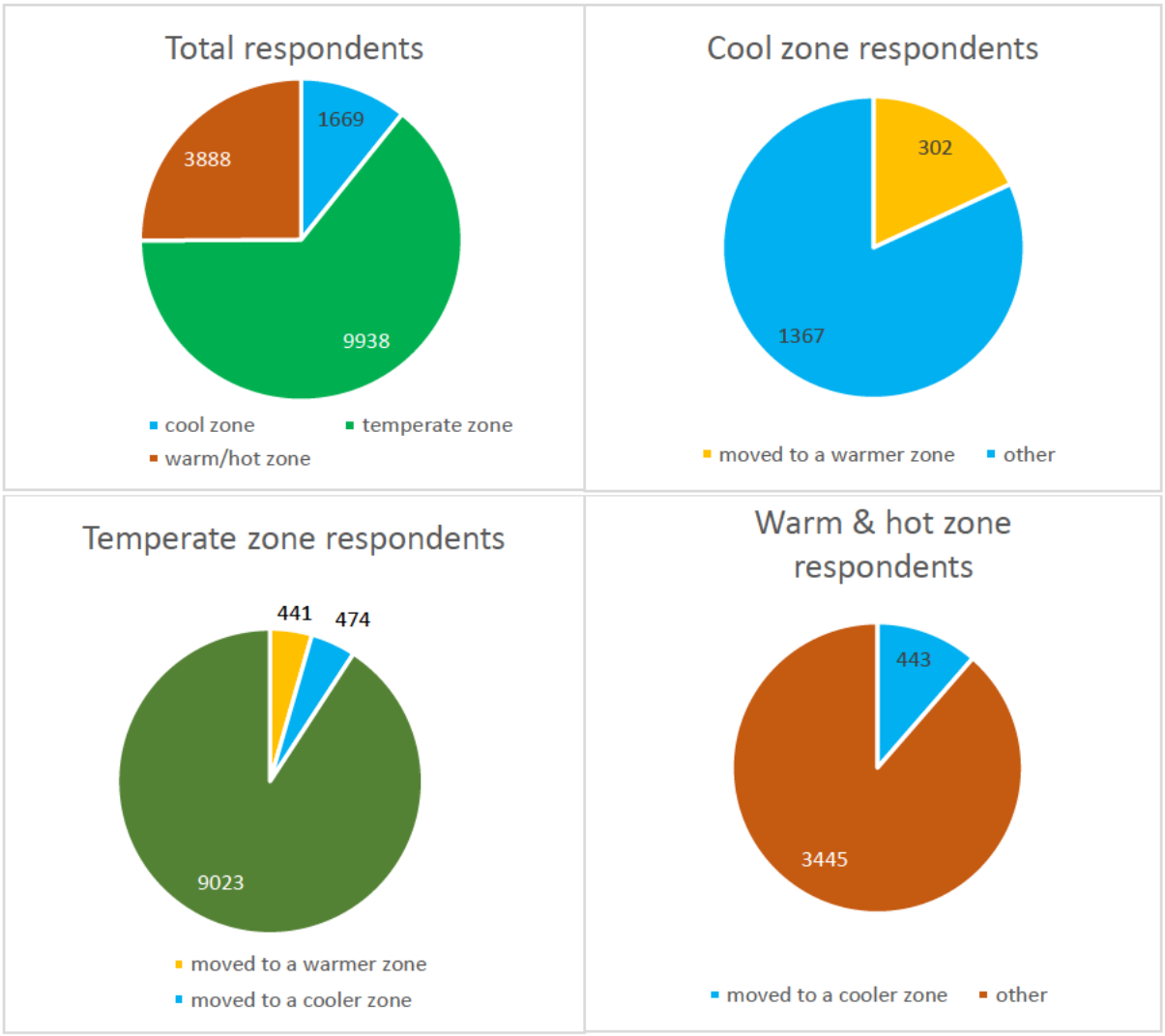

Figure 6-2: Residential mobility: climate zones

6.4.1.2 Personality traits and life satisfaction

As would be expected, mean values for personality traits vary little over the three baseline years of measurement since theory posits that personality is a fixed individual characteristic (Costa & McCrae, 1998). Average extraversion and openness to experience decrease slightly between 2013 and 2021 while average emotional stability increases a little. Variations around the mean are similar between baseline years. LS scores averaged at 7.95 (on a 1-10 scale; scores are stable across baseline years) (Table 6-4).

Table 6-2: Personality traits and LS mean score and standard deviation for baseline years

Baseline year	**2013**		**2017**		**2021**	
	mean	SD	mean	SD	mean	SD
extraversion (1-7)	4.431	1.091	4.412	1.095	4.361	1.089
agreeableness (1-7)	5.448	0.908	5.412	0.933	5.394	0.961
conscientiousness (1-7)	5.124	1.023	5.115	1.025	5.144	1.023
emotional stability (1-7)	5.191	1.087	5.215	1.077	5.277	1.107
openness to experience (1-7)	4.249	0.908	4.201	0.933	4.136	0.961
life satisfaction (0-10)	7.946	1.399	7.954	1.393	7.955	1.393

6.4.1.3 Socio-demographic variables

The basic demographic indicators (marital status, gender, children) are stable over the period of study (Table 6-3). Education levels change significantly between 2013 and 2021 with 32% holding a tertiary degree in 2021 compared to 25% in 2013. Unemployment decreases from 3.44% to 2.46% over the period of study, well below the national average but reflecting the national trend (5.6% to 5.1%) (World Bank, 2023a). In nominal dollar terms, average household income for our sample rose from $113,000 to $144,000. The median household income for the whole Australian population rose from $107,000 to $139,000 during the same period (Australian Bureau of Statistics, 2022). Thus, the change of income for households in the sample over the study period reflects the national trend. The percentage of respondents affected by life events varies over the period with about 20% reporting a favourable life event and about 40% reporting an adverse life event.

Table 6-3: Socio-demographic variables for baseline years

	2013		**2017**		**2021**	
	n	%	n	%	n	%
married/ de facto	8,103	61.32	7,566	62.50	7,671	63.37
have children	3,931	29.75	3,615	29.86	3,313	27.37
female	7,106	53.78	6,547	54.08	6,547	54.08
education:						
university	3,351	25.37	3,540	29.26	3,880	32.07
unemployed	454	3.44	338	2.79	298	2.46
favourable life event	2,895	21.96	2,787	23.05	2,164	17.9
adverse life event	5,626	42.59	4,832	39.97	4,780	39.54
	mean	SD.	mean	SD	mean	SD.
household income ($k)	113.70	103.3	130.60	156.10	144.70	166.10
age (years)	45.42	18.31	46.20	18.10	50.20	18.10

6.4.2 Selective mobility

6.4.2.1 Selective mobility between rural and urban area

Two sets of models were estimated: the first set predicts the probability for people residing in a rural area in the baseline year to move to an urban area; the second model estimates the probability for residents of urban areas to move to a rural area. Table 6-4 only reports results for the fully adjusted models.[83] Results for the rural residents' cohort show that LS scores before the move are not significantly associated with a move from a rural area to an urban area. For urban residents, lower LS scores before the move are significantly associated with a move from an urban area to a rural area, although the coefficient is only weakly significant in the fully adjusted model. Conversely, urban residents with higher LS scores are less likely to move to a rural area.

Table 6-4: Association between LS score before the move and selective mobility to city or rural

	Fully adjusted model			**Fully adjusted model**		
Number of observations	N=30,963			N=63,446		
Number of respondents	n=5,114			n=10,284		
Cohort	Rural residents			Urban residents		
Dependent variable	**move to city**			**move to rural**		
	OR	CI		OR	CI	
life satisfaction (n-1)	1.014	0.965	1.065	*0.957**	*0.914*	*1.003*
extraversion	1.083	0.997	1.178	1.036	0.963	1.114
agreeableness	0.944	0.866	1.028	**0.900****	**0.834**	**0.971**
conscientiousness	1.028	0.943	1.121	1.065	0.983	1.155
emotional stability	0.962	0.879	1.054	0.992	0.912	1.079
openness to experience	**1.097****	**1.002**	**1.202**	1.061	0.977	1.152
age (square)	**0.964****	**0.981**	**0.971**	**0.981****	**0.976**	**0.986**
female	0.979	1.032	1.158	1.032	0.887	1.201
married	**0.706****	0.993	**0.838**	0.993	0.838	1.176
children	**0.563****	*0.855*	**0.689**	*0.855*	*0.716*	*1.020*
education status	**1.149****	1.012	**1.243**	1.012	0.941	1.088
household income	**0.996****	**0.996**	**0.998**	**0.996****	**0.995**	**0.998**
unemployed	**1.597****	**1.796**	**2.227**	**1.796****	**1.316**	**2.451**
life events (fav)	**2.323****	**2.491**	**2.752**	**2.491****	**2.137**	**2.904**
life events (adverse)	0.943	1.027	1.115	1.027	0.884	1.191

Table shows **odd ratio** and confidence interval for each variable; ** indicates significance p<0.05, * indicates significance p<0.10

[83] The results for all models can be found in the appendix (Section 6.7).

Personality traits are not generally significant predictors of selective mobility to a rural/ urban area in the fully adjusted models apart for openness to experience that is positively associated with a move from rural to the city. Age is a negative predictor of a move to a different type of residence confirming the prevalence of mobility among young residents. Being unemployed is a strong positive predictor of selective moves of any form, but families with children are less likely to move. A higher education level is a predictor of a move from rural to urban but not of a move from the city to rural. The occurrence of a favourable life event is positively associated with selective mobility, however adverse life events has apparently no influence.

The same models as above were estimated using a dataset comprising only people who moved during the period rather than all residents (results not shown). I found that LS scores before the move are not a significant predictor of a choice between moving to the city or moving to another rural area for rural residents. The model for urban residents showed a significant association between lower LS scores before the move and the choice to move to the country, however the coefficient becomes non-significant in the fully adjusted model.

6.4.2.2 Selective mobility to a different climate zone

I estimated two sets of models predicting selective mobility to a warmer climate and then to a cooler zone. Results shown in Table 6-5 are for the fully adjusted models. Lower LS scores before the move are significantly associated with mobility to a warmer climate zone for people residing in a cool or temperate zone at baseline time, however the coefficient becomes weakly significant in the fully adjusted model. Lower LS scores before the move are also significantly associated with mobility to a cooler zone for people who resided in the warm or the hot zone, at baseline time.

None of the personality traits are significant predictors of a selective move to another climate zone in the fully adjusted models. As for the previous set of models predicting selecting moves to rural or urban areas, age is a significant factor with a negative sign indicating that younger people choose to move a different climate zone. Other socio-demographic variables such as unemployment and having children behave similarly as in the selective mobility models for rural/ urban. Favourable life events are again positively associated with selective mobility.

The same models as above were estimated using a dataset comprising only people who moved during the period rather than all individuals (results not shown). For both sets of

models, LS scores prior to the move are significantly associated with selective mobility to a different climate zone: i.e., people dissatisfied with their lives are more likely to selectively move to a different climate zone.

Table 6-5: Association between LS score before the move and selective mobility to a different climate zone

	Fully adjusted model			**Fully adjusted model**		
Number of observations	N=70,881			N=24,308		
Number of respondents	n=11,541			n=3,880		
Cohort	Cool/ temp zone residents			Warm/hot zone residents		
Dependent variable	**move to a warmer climate**			**move to a cooler climate**		
	OR	CI		OR	CI	
life satisfaction (n-1)	*0.962**	*0.919*	*1.007*	**0.930****	**0.881**	**0.982**
extraversion	1.040	0.966	1.120	1.071	0.964	1.188
agreeableness	0.938	0.864	1.018	1.026	0.922	1.142
conscientiousness	1.016	0.939	1.099	1.041	0.939	1.155
emotional stability	1.018	0.936	1.107	1.002	0.893	1.126
openness to experience	1.072	0.986	1.166	1.032	0.925	1.151
age (square)	**0.968****	**0.963**	**0.974**	**0.969****	**0.961**	**0.977**
female	1.019	0.882	1.177	1.121	0.908	1.384
married	0.900	0.776	1.044	0.954	0.776	1.173
children	**0.789****	**0.671**	**0.927**	**0.783****	**0.629**	**0.976**
education status	*1.063**	0.995	1.136	**1.168****	**1.054**	**1.295**
household income	**0.995****	**0.994**	**0.996**	**0.997****	**0.996**	**0.999**
unemployed	**1.696****	**1.288**	**2.232**	**1.636****	**1.107**	**2.419**
life events (fav)	**2.158****	**1.876**	**2.482**	**2.352****	**1.925**	**2.874**
life events (adverse)	1.008	0.879	1.155	0.944	0.779	1.144

Table shows **odd ratio** and CI for each variable: ** indicates significance p<0.05; * significance level p<0.1.

6.4.3 Social and ecological influence

Models predicting LS trajectory in the years after baseline measurement were estimated for type of residence (rural/ urban) and climate zone (warmer/ cooler). All models used FE (within-individual) estimators. I used the dataset of "movers" to estimate social influence on LS trajectory. Results are shown here for fully adjusted models with all models presented in the appendix (Section 6.7).

6.4.3.1 Social and ecological influence of type of residence (rural/ urban) on LS

For models predicting the influence of moving to a rural residence, I used respondents who lived in an urban area at baseline time and moved during the period; correspondingly, I predicted the influence of moving to an urban residence for the cohort of respondents who resided in an urban area at baseline time and moved during the period.

For urban residents who moved to a rural area, living in a rural area has a positive effect on their LS trajectory when controlling for personality traits and socio-economic factors. Conversely the influence of living in an urban area for rural residents who moved to a rural area has no significant influence on their LS trajectory over the period (Table 6-6).

Extraversion, agreeableness, and emotional stability have a positive influence on the LS trajectory of people who moved from an urban area regardless of where they moved. Emotional stability is the only personality trait with a significant (positive) influence on the LS trajectory for residents who moved from a rural area. Socio-demographic control variables had similar positive coefficients for the two sets of models.

6.4.3.2 Ecological influence of climate zone on LS

For models predicting the influence of moving to a warmer climate zone, I used respondents who lived in the temperate or cool zone at baseline time and moved during the period; likewise, I predicted the influence of moving to a cooler zone for the cohort of respondents who resided in warm or hot zone and moved during the period.

For people residing in a cool or temperate zone who moved to a warmer climate, living in warmer climate is associated with a positive influence on their LS trajectory. However, for people residing in a warm or hot zone who moved to a cooler climate, living in a cooler climate had no significant influence on their LS trajectory (Table 6-7). Extraversion, agreeableness, and emotional stability have a positive effect on LS trajectory of residents of a cool or temperate zone who moved regardless of where they moved. For people who moved from a warm or hot region, only emotional stability had a significant (positive) effect. The influence of socio-demographic factors on LS trajectory was similar for both cohorts.

Table 6-6: Predictors of LS within-individual trajectory for residents who moved: urban/ rural

	Fully adjusted model			**Fully adjusted model**		
Number of observations	N=38,162			N=18,485		
Number of respondents	n=5,239			n=2,582		
cohort	Urban residents who moved			Rural residents who moved		
Adjusted R^2*	Adj. R^2 =0.3579			Adj. R^2 =0.3024		
LS (dep var)	**Coeff.**	**CI**		**Coeff.**	**CI**	
urban residence	**-**	**-**	**-**	-0.019	-0.112	0.074
rural residence	**0.076****	**0.002**	**0.150**	**-**	**-**	**-**
extraversion	**0.049****	**0.014**	**0.084**	0.045	-0.010	0.100
agreeableness	**0.047****	**0.017**	**0.078**	0.013	-0.033	0.059
conscientiousness	-0.009	-0.042	0.023	*0.046*	-0.005	0.097
emotional stability	**0.088****	**0.056**	**0.119**	**0.093****	**0.045**	**0.141**
openness to experience	0.010	-0.026	0.045	0.043	-0.011	0.097
married	**0.178****	**0.126**	**0.230**	**0.137****	**0.050**	**0.225**
health status	**0.280****	**0.256**	**0.303**	**0.271****	**0.233**	**0.308**
household income	**0.001****	**0.001**	**0.001**	**0.002****	**0.002**	**0.002**

Table shows **coefficient** and CI for each variable; ** indicates significance p<0.05; * significance p<0.10
* Reported adjusted R^2 was calculated in STATA using absorbing indicators:
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

Table 6-7: Predictors of LS within-individual trajectory for residents who moved: climate zone

	Fully adjusted model			**Fully adjusted model**		
Number of observations	N=41,479			N=15,168		
Number of respondents	n=5,698			n=2,123		
Cohort	'movers' from a cool/ temperate zone			'movers' from a warm/hot zone		
Adjusted R^2*	Adj. R^2 =0.3486			Adj. R^2 =0.3087		
LS (dep var)	**Coeff.**	**CI**		**Coeff.**	**CI**	
Cool/ temp zone residence	**-**	**-**	**-**	0.012	-0.103	0.127
warm zone residence	**0.142****	**0.040**	**0.245**	**-**	**-**	**-**
extraversion	**0.059****	**0.025**	**0.093**	0.020	-0.040	0.080
agreeableness	**0.045****	**0.016**	**0.075**	0.009	-0.042	0.059
conscientiousness	0.011	-0.020	0.042	0.007	-0.048	0.063
emotional stability	**0.087****	**0.056**	**0.117**	**0.094****	**0.041**	**0.147**
openness to experience	0.016	-0.019	0.051	0.033	-0.026	0.092
married	**0.168****	**0.115**	**0.220**	**0.160****	**0.070**	**0.251**
health status	**0.269****	**0.246**	**0.293**	**0.298****	**0.258**	**0.338**
household income	**0.001****	**0.001**	**0.001**	**0.001****	**0.001**	**0.002**

Table shows **coefficient** and CI for each variable; ** indicates significance p<0.05; * significance p<0.10.
* Reported adjusted R^2 was calculated in STATA using absorbing indicators
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

6.5 Discussion

As, to the best of my knowledge, no prior study examined the relationship between happiness levels and *selective* geographic mobility within the same country, direct

comparisons of results are difficult. The findings from this study suggest that lower LS scores before the move predicts two specific geographic migrations within the same country: a move from the city to a rural area and a move to a region with a different climate. This outcome appears consistent with findings by Nowok et al. (2013) that for people who choose to move, there is generally a low point in happiness level prior to the move. However we need to be cautious when interpreting these findings: moving to the country or to a region with a warmer climate may be a conscious lifestyle decision that people make when they are not happy with their life in the city, or when they wish to live in a sunnier, warmer place; but it may also be a decision imposed by circumstances (work, study) rather than a deliberate choice. A move from Sydney (temperate zone) to Brisbane (warm zone) may be motivated by nothing other than a job opportunity!

To assess whether the pattern of relationship between LS scores and selective mobility is influenced by the move reason, I estimated the selective mobility models while including a dummy variable for 'moving for work reason'. The results (not shown) indicate no significant relationship between pre-move LS scores and a move to rural or a move to a warmer climate. Conversely, lower LS levels before the move are significantly associated with a move to the city or a move to a cooler region. This outcome suggests that when people move from the country to the city or when they move to a cooler climate, it is more likely that the reason behind the move is job related.

Results from our social and ecological influence models suggest that moving from the city to a rural area or moving to a region with a warmer climate is associated with an uplift in the individual's LS trajectory. Again, as this type of relationship has never been investigated before, direct comparison of results is difficult. However this outcome is consistent with previous findings from research in Australia, the US and Canada that report the positive influence of rural living on LS (Cummins et al., 2003; R. Fernandez & Kulik, 1981; Helliwell et al., 2019). It also confirms existing evidence showing that higher temperatures have a positive effect on LS for people who normally live in cooler areas (Maddison & Rehdanz, 2011). Finally, it aligns with earlier findings by Rappaport (2007) indicating that US residents move to places with "nicer weather" to maximise their quality of life; and with evidence that people in Europe value sunny climate as an amenity (Maddison & Bigano, 2003; Moro et al., 2008).

The overall picture that comes out of these findings is that people who are unhappy with city life are more likely to choose to migrate to a rural area. Once they have moved

there, their LS trajectory registers an upward lift, seemingly confirming the beneficial impact of the move. The same interpretation can apply to people who are unhappy with living in a cool area and decide to move to a warmer region. This pattern in subjective individual wellbeing path may not be limited to selective mobility as it reflects a pattern observed by Nowok et al. (2013) for all internal migrants in the UK: the move happens after a period of stress with low levels of happiness and is followed with an improvement in happiness levels, although the same study noted that the improvement may only be transitory. The findings from this study are also consistent with previous evidence that places with higher levels of happiness wellbeing attract more migrants (Hummel, 2016).

The role of personality traits in predicting selective mobility appears to be limited when these variables are included with LS scores and socio-demographic factors. The only two personality variables with significant coefficients were agreeableness, negatively associated with a move from the city to a rural area, and openness to experience positively associated with a move from the country to the city. Jokela (2020) who used a similar dataset but did not include LS as an explanatory factor had openness to experience along with conscientiousness and extraversion predicting a move to the city. The positive association between openness to experience and a move to the city can be explained by the fact that if you are open to experience, you are more likely to be willing to experiment new ideas and thus be more adventurous and willing to move to new places (Silvia & Christensen, 2020). Conversely, people with high levels of agreeableness are more likely to stay in the same place for a long time as they value the relationships they have developed (Jokela, 2009, 2014).

The influence of socio-demographic factors on selective mobility decisions reflect their influence on internal migration decisions reported elsewhere (Hummel, 2016; Nowok et al., 2013). A noteworthy outcome from this research is the lack of significance of the 'female' factor in all models. According to the migration literature (Castorina & Welters, 2022), women are more likely to be 'tied movers' and as such, one could expect that they would be less likely to see an uplift of their LS trajectory after the move compared to men. However Nowok et al. (2013) report no differences between men and women in subjective wellbeing trajectory after migration even where women are tied movers.

6.6 Conclusion

The objective of this chapter was to investigate the possible impact of selective mobility, and social and ecological influence on the geographic clustering of LS scores. From this general objective I derived several research questions. In the analysis, I control for

individual socio-economic characteristics and personality traits as those variables have been shown to influence mobility decision.

In terms of selective mobility, the results show that lower LS scores before the move are associated with a higher probability of a move to a rural area for urban residents; however, LS scores do not seem to influence a move to the city for rural residents (RQ_1). I also find evidence of an association between lower LS scores before the move and a decision to move to a region with a different climate (RQ_2). This is true regardless of whether the region of destination has a warmer or cooler climate.

In the second phase of the study, I investigate the possible social and ecological influence that a specific type of residence may have on the LS of people who moved. I find that a move from the city to a rural area is associated with an uplift in LS trajectory over time for the individual (RQ_3). A move from a cool or temperate region to a warmer climate is associated with a similar uplift in LS trajectory (RQ_5). Conversely a move from a rural area to the city, or a move to a cooler region has apparently no effect on LS.

Several limitations that could hamper the interpretation and generalisation of the results are acknowledged. Firstly, the classification between rural and urban areas relies on a remoteness criterion, which is a crude way of defining 'rurality'. Mid-size regional cities such as Townsville or Cairns with a population over 150,000 display features such as density, social infrastructure that many would recognise as urban; however, they are classified as a rural in my analysis. Secondly, the climate zone classification retained for this study relies on temperature thresholds that may not accurately reflect all the characteristics of each climate zone: for instance, a warm area may be dry and sunny or alternatively rainy and humid. Finally, the analysis only incompletely addresses the various reasons why people choose to move. Jokela (2021) shows that the influence of different personality traits on the decision to move is dependent on the reasons behind the move. There is no reason to believe that the association between LS and specific types of selective mobility is not also moderated by the reason behind the move. Further research that differentiates between reasons for moving would provide further insight into this issue.

Despite these limitations, this study makes an important contribution to both the economics of wellbeing literature and the literature on internal migration. To the best of my knowledge, it is first study that investigates the role of LS on selective geographic mobility

within the same country, and that analyses the impact of a such move on LS trajectory. It is also the first time that the effect of a move to a different climate zone on LS is examined.

The outcomes from this research show that when people choose to migrate to regions that they perceive as attractive, they tend to do so after a period where they may feel stressed, with the expectation that the move will make them happier. The results suggest that overall, the move may fulfil these expectations. Thus, LS scores of people who wish to move may be an indicator of where they will choose to move. This knowledge could be useful in helping demographers project future population movements from metropolitan areas to "regional areas" and to warmer climes. Recent population statistics appear to support the attraction of moving to the rural areas and to a sunny climate (Australian Bureau of Statistics, 2023a). My findings may also assist in the development of policies that aim to promote living in regional areas by identifying wellbeing and psychological factors that motivate people to selectively move to these areas. Conversely, a better knowledge about push factors in regions that people are leaving may help address these problems.

6.7 Appendix to Chapter 6

6.7.1 Selective mobility: results for all models

Table 6-8: Association between LS score before the move and selective mobility to the city for rural residents (all models)

move_city (dep var)	**LS only**			**Personality adjusted**			**Fully adjusted**		
Number of observations	N=32,268			N=32,268			N=30,963		
Number of respondents	n=5,158			n=5,158			n=5,114		
	OR	CI		OR	CI		OR	CI	
life satisfaction (n-1)	**0.950****	**0.915**	**0.987**	0.970	0.932	1.011	1.014	0.965	1.065
extraversion				**1.190****	**1.096**	**1.293**	1.083	0.997	1.178
agreeableness				**0.904****	**0.834**	**0.979**	0.944	0.866	1.028
conscientiousness				0.953	0.878	1.034	1.028	0.943	1.121
emotional stability				**0.850****	**0.785**	**0.921**	0.962	0.879	1.054
openness to experience				**1.188****	**1.088**	**1.297**	**1.097****	**1.002**	**1.202**
age (square)							**0.964****	**0.958**	**0.971**
female							0.979	0.828	1.158
married							**0.706****	**0.594**	**0.838**
children							**0.563****	**0.459**	**0.689**
education status							**1.149****	**1.063**	**1.243**
household income							**0.996****	**0.995**	**0.998**
unemployed							**1.597****	**1.146**	**2.227**
life events (fav)							**2.323****	**1.961**	**2.752**
life events (adverse)							0.943	0.798	1.115

Table shows **odd ratio** and CI for each variable: ** indicates significance p<0.05; * significance level p<0.1.

Table 6-9: Association between LS score before the move and selective mobility to rural for urban residents (all models)

move_rural (dep var)	**LS only**			**Personality adjusted**			**Fully adjusted**		
Number of observations	N=65,402			N=65,402			N=63,446		
Number of respondents	n=10,335			n=10,335			n=10,284		
	OR	CI		OR	CI		OR	CI	
life satisfaction (n-1)	**0.926****	**0.898**	**0.976**	**0.936****	**0.898**	**0.976**	*0.957**	*0.914*	*1.003*
extraversion				**1.108****	**1.030**	**1.191**	1.036	0.963	1.114
agreeableness				**0.870****	**0.808**	**0.937**	**0.900****	**0.834**	**0.971**
conscientiousness				0.991	0.917	1.070	1.065	0.983	1.155
emotional stability				**0.911****	**0.843**	**0.986**	0.992	0.912	1.079
openness to experience				**1.090****	**1.008**	**1.179**	1.061	0.977	1.152
age (square)							**0.981****	**0.976**	**0.986**
female							1.032	0.887	1.201
married							0.993	0.838	1.176
children							*0.855*	*0.716*	*1.020*
education status							1.012	0.941	1.088
household income							**0.996****	**0.995**	**0.998**
unemployed							**1.796****	**1.316**	**2.451**
life events (fav)							**2.491****	**2.137**	**2.904**
life events (adverse)							1.027	0.884	1.191

Table shows **odd ratio** and CI for each variable: ** indicates significance p<0.05; * significance level p<0.1.

Table 6-10: Association between LS score before the move and selective mobility to a warmer climate zone for residents of cool or temperate zones (all models)

move_warm (dep v.)	**LS only**			**Personality adjusted**			**Fully adjusted**		
Number of observ.	N=73,470			N=73,470			N=70,881		
Number of respond.	n=11,619			n=11,619			n=11,541		
	OR	CI		OR	CI		OR	CI	
life satisfaction(n-1)	**0.931****	**0.896**	**0.967**	**0.944****	**0.906**	**0.982**	*0.962**	*0.919*	*1.007*
extraversion				**1.113****	**1.035**	**1.197**	1.040	0.966	1.120
agreeableness				**0.907****	**0.839**	**0.980**	0.938	0.864	1.018
conscientiousness				0.950	0.881	1.025	1.016	0.939	1.099
emotional stability				**0.907****	**0.840**	**0.980**	1.018	0.936	1.107
openness to experience				**1.101****	**1.016**	**1.193**	1.072	0.986	1.166
age (square)							**0.968****	**0.963**	**0.974**
female							1.019	0.882	1.177
married							0.900	0.776	1.044
children							**0.789****	**0.671**	**0.927**
education status							*1.063**	0.995	1.136
household income							**0.995****	**0.994**	**0.996**
unemployed							**1.696****	**1.288**	**2.232**
life events (fav)							**2.158****	**1.876**	**2.482**
life events (adverse)							1.008	0.879	1.155

Table shows **odd ratio** and CI for each variable: ** indicates significance p<0.05; * significance level p<0.1.

Table 6-11: Association between LS score before the move and selective mobility to a cooler climate zone for residents of warm or hot zones (all models)

move_cool (dep var)	**LS only**			**Personality adjusted**			**Fully adjusted**		
Number of observ.	N=24,368			N=24,368			N=24,308		
Number of respond.	n=3,888			n=3,888			n=3,880		
	OR	CI		OR	CI		OR	CI	
life satisfaction (n-1)	**0.915****	0.872	0.960	**0.917****	0.873	0.963	**0.930****	0.881	0.982
extraversion				**1.178****	1.057	1.312	1.071	0.964	1.188
agreeableness				0.988	0.889	1.098	1.026	0.922	1.142
conscientiousness				0.981	0.883	1.091	1.041	0.939	1.155
emotional stability				*0.900*	0.806	1.005	1.002	0.893	1.126
openness to experience				*1.102*	0.988	1.229	1.032	0.925	1.151
age (square)							**0.969****	**0.961**	**0.977**
female							1.121	0.908	1.384
married							0.954	0.776	1.173
children							**0.783****	**0.629**	**0.976**
education status							**1.168****	**1.054**	**1.295**
household income							**0.997****	**0.996**	**0.999**
unemployed							**1.636****	**1.107**	**2.419**
life events (fav)							**2.352****	**1.925**	**2.874**
life events (adverse)							0.944	0.779	1.144

Table shows **odd ratio** and CI for each variable: ** indicates significance p<0.05; * significance level p<0.1.

6.7.2 Social and ecological influence: results for all models

Table 6-12: Predictors of LS within-individual trajectory for urban residents who moved (all models)

	Type of residence			**Personality adjusted**			**Fully adjusted**		
Number of observations	N=39,596			N=39,542			N=38,162		
Number of respondents	n=5,242			n=5,239			n=5,239		
Adjusted R^2*	Adj. R^2 =0.3387			Adj. R^2 =0.3398			Adj. R^2 =0.3579		
LS (dep var)	**Coeff**	**CI**		**Coeff**	**CI**		**Coeff.**	**CI**	
rural residence	*0.065**	-0.009	0.138	0.059	-0.015	0.132	**0.076****	**0.002**	**0.150**
extraversion				**0.055****	**0.020**	**0.090**	**0.049****	**0.014**	**0.084**
agreeableness				**0.051****	**0.021**	**0.082**	**0.047****	**0.017**	**0.078**
conscientiousness				0.004	-0.028	0.036	-0.009	-0.042	0.023
emotional stability				**0.093****	**0.061**	**0.124**	**0.088****	**0.056**	**0.119**
openness to experience				0.008	-0.028	0.044	0.010	-0.026	0.045
married							**0.178****	**0.126**	**0.230**
health status							**0.280****	**0.256**	**0.303**
household income							**0.001****	**0.001**	**0.001**

Table shows **coefficient** and CI for each variable; ** indicates significance p<0.05; * significance p<0.10

* Reported adjusted R2 was calculated in STATA using absorbing indicators:
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

Table 6-13: Predictors of LS within-individual trajectory for rural residents who moved (all models)

	Type of residence			Personality adjusted			Fully adjusted		
Number of observations	N=19,376			N=19,346			N=18,485		
Number of respondents	n=2,584			n=2,583			n=2,582		
Adjusted R^2*	Adj. R^2=0.2813			Adj. R^2=0.2839			Adj. R^2=0.3024		
LS (dep var)	**Coeff**	**CI**		**Coeff**	**CI**		**Coeff.**	**CI**	
urban residence	-0.073	-0.165	0.019	-0.070	-0.162	0.022	-0.019	-0.112	0.074
extraversion				*0.050**	*-0.005*	*0.104*	0.045	-0.010	0.100
agreeableness				0.013	-0.033	0.059	0.013	-0.033	0.059
conscientiousness				**0.066****	**0.016**	**0.117**	*0.046**	-0.005	0.097
emotional stability				**0.101****	**0.053**	**0.149**	**0.093****	**0.045**	**0.141**
openness to experience				0.037	-0.017	0.091	0.043	-0.011	0.097
married							**0.137****	**0.050**	**0.225**
health status							**0.271****	**0.233**	**0.308**
household income							**0.002****	**0.002**	**0.002**

Table shows **coefficient** and CI for each variable; ** indicates significance p<0.05; * significance p<0.10

* Reported adjusted R2 was calculated in STATA using absorbing indicators:
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

Table 6-14: Predictors of LS within-individual trajectory for residents of cool or temperate zones who moved (all models)

	Climate zone			Adjusted for personality			Fully adjusted		
Number of observations	N=43,204			N=43,146			N=41,479		
Number of respondents	n=5,702			n=5,699			n=5,698		
Adjusted R^2*	Adj. R^2 =0.3296			Adj. R^2 =0.3312			Adj. R^2 =0.3486		
LS (dep var)	**Coeff**	**CI**		**Coeff**	**CI**		**Coeff.**	**CI**	
warm zone residence	**0.136****	0.029	0.232	**0.130****	**0.029**	**0.232**	**0.142****	**0.040**	**0.245**
extraversion				**0.059****	**0.025**	**0.093**	**0.059****	**0.025**	**0.093**
agreeableness				**0.048****	**0.018**	**0.078**	**0.045****	**0.016**	**0.075**
conscientiousness				0.026	-0.005	0.058	0.011	-0.020	0.042
emotional stability				**0.089****	**0.058**	**0.119**	**0.087****	**0.056**	**0.117**
openness to experience				0.015	-0.020	0.050	0.016	-0.019	0.051
married							**0.168****	**0.115**	**0.220**
health status							**0.269****	**0.246**	**0.293**
household income							**0.001****	**0.001**	**0.001**

Table shows **coefficient** and CI for each variable; ** indicates significance p<0.05; * significance p<0.10.

* Reported adjusted R2 was calculated in STATA using absorbing indicators
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

Table 6-15: Predictors of LS within-individual trajectory for residents of warm or hot zones who moved (all models)

	Climate zone			**Adjusted for personality**			**Fully adjusted**		
Number of observations	N=15,768			N=15,742			N=15,168		
Number of respondents	n=2,124			n=2,123			n=2,123		
Adjusted R^2*	Adj. R^2 =0.2872			Adj. R^2 =0.2889			Adj. R^2 =0.3087		
LS (dep var)	**Coeff**	**CI**		**Coeff**	**CI**		**Coeff.**	**CI**	
temperate zone residence	-0.028	-0.142	0.086	-0.030	-0.144	0.083	0.012	-0.103	0.127
extraversion				0.038	-0.023	0.098	0.020	-0.040	0.080
agreeableness				0.013	-0.037	0.063	0.009	-0.042	0.059
conscientiousness				0.023	-0.033	0.078	0.007	-0.048	0.063
Emotional stability				**0.112****	**0.059**	**0.165**	**0.094****	**0.041**	**0.147**
openness to experience				0.027	-0.032	0.085	0.033	-0.026	0.092
married							**0.160****	**0.070**	**0.251**
health status							**0.298****	**0.258**	**0.338**
household income							**0.001****	**0.001**	**0.002**

Table shows coefficient and CI for each variable; **indicates significance p<0.05; * significance level p<0.1.

* Reported adjusted R^2 was calculated in STATA using absorbing indicators
https://www.stata.com/support/faqs/statistics/areg-versus-xtreg-fe/

Chapter 7 Conclusion

7.1 Introduction

In this chapter I summarize the findings from the studies included in this thesis and highlight the contribution made by the research in terms of advancement of knowledge and practical applications. I also acknowledge the limitations of the research and make suggestions for future research.

I started this thesis by observing that improving human wellbeing was recognized as a key benchmark of good policy making, and that designing effective and appropriate policies required a good understanding of the factors that contribute to subjective wellbeing, and the ability to define and measure the relationship between these factors and subjective wellbeing. In other words, the central objective of wellbeing research is to find answers to the questions: "What makes people happy?"; and "to what extent do these factors contribute to people's happiness?" These questions have often been answered in the traditional economics literature by attempts to maximize "utility" and by politicians and policymakers in the form of policies that stimulate GDP growth. However, as I argue in Chapter 2, there is now a growing acknowledgement that GDP is a somewhat "narrow" and in many ways flawed concept and that the acceptance of GDP as a valid proxy to represent human wellbeing ignores the many other dimensions that contribute to what Herman Daly called "the good life" (Victor, 2022). The previous statement must be tempered somewhat in view of evidence showing that the relationship between GDP and LS may vary depending on culture on overall development of the country. A study recently undertaken across several Asian countries indicates that Standard of living (reflecting individual income but also overall level of development) was a key driver of LS. (Yee et al., 2015)

As discussed in Chapter 2 (Section 2.2.2), subjective wellbeing is an umbrella term for many overlapping but conceptually distinctive dimensions that have sometimes been used interchangeably in the economics of wellbeing and economics of happiness literature. In that chapter, I also justify the choice of the life satisfaction (LS) concept to represent wellbeing on the ground that it is closely aligned with utility, and as such it has been favoured by most wellbeing economists.

The object of empirical research in the discipline of wellbeing/happiness economics has been primarily to identify contributing factors and model their relationship with a dependent variable representing LS. The contribution of this thesis fits within this broad objective. Its specific purpose lies in expanding our knowledge about how geographic diversity in those contributing factors may affect the relationship with LS. This diversity may relate to contextual factors representing the natural environment, particularly the climate, as well as disparities in the social context; but it may also be due to compositional effects: i.e., people living at different locations have different characteristics and different perceptions. This general objective informed my review of the literature and helped me identify several research gaps from which I was able to articulate the four specific research objectives identified in Chapter 1.

I start my research by investigating the contextual factors identified in the inner circles of the Venn diagram represented in Figure 1-1 of Chapter 1. Firstly, in Chapter 3, I revisit the relationship between climate and LS previously examined in inter-country studies by Rehdanz and Maddison (2005) and Maddison and Rehdanz (2011), but by conducting this investigation within a single jurisdiction, I eliminate the possible interference of diverse cultural and social factors. I also extend previous research by exploring the possible spatial non-stationarity in the relationship between climate factors and LS. Then, in Chapter 4, I focus on the influence of social capital factors on LS at neighbourhood level. The main innovations of this study are that: (i) it considers several dimensions of social capital instead of a single variable; (ii) it examines the influence of these variables on LS at multiple levels of interaction; (iii) the analysis is conducted at a small scale of observation (neighbourhood) within an urban context. The research then moves to the outer circles of the Venn diagram, first investigating how individuals perceive their environment and how this perception influences LS, then focusing on the characteristics of individuals moving to, and residing at specific locations. The study in Chapter 5 contributes to the ongoing research about the influence of subjective and objective factors on wellbeing by examining the interface between objective climate and environmental attributes and subjective perceptions of these attributes, and how each type contributes to overall LS. The focus of the study in Chapter 6 is on compositional effects. Here, I attempt to explain spatial diversity and clustering in LS levels by looking at the possible reasons why on average people who share similar LS profiles are found in specific regions. To this intent, I apply a framework of analysis that has

previously been used to explain spatial clustering in psychological traits, but to my knowledge, has never been applied to LS.

The remainder of this chapter is structured as follows. In the next section (Section 7.2), I present a synopsis of the key findings from each of the four studies included in this thesis. Then, in Section 7.3, I highlight the contribution of my research to knowledge as well as the methodological contributions and the practical implications of my findings. The last two sections are devoted to discussing the limitations of my research (Section 7.4) and suggesting ideas for future research building on the findings from this thesis (Section 7.5).

7.2 Synopsis of key findings

7.2.1 Summary of Chapter 3_ Does the climate impact satisfaction with life?

The objective of this chapter was to assess how locally observed climate variables within a single large country contribute to individual LS while controlling for socio-demographic factors. This general objective is addressed through two consecutive steps. In the first step, I estimate five alternative OLS models where climate variables are entered under different measure types reflecting either average, intensity, or duration. One of the models uses two composite climate factors determined through Principal Component Analysis. The two factors built from a basket of primary climate variables are identified as Climate Factor 1 and Climate Factor 2 respectively representing 'hot and dry' and 'wet and warm' conditions. In the second step, having tested for the spatial non-stationarity of the general OLS models, I apply Geographically Weighted Regression (GWR) to estimate local relationship patterns between climate contributors and LS in each spatial unit, here level 2 statistical areas.

The five general OLS models have very close adjusted R^2 and AIC values. Climate variables are found to be significant contributors of LS in every model, but the best fit is obtained when climate variables are included in a non-linear form. The broad outcome is that higher temperatures are associated with lower LS levels; conversely higher rainfall and sunshine have a positive influence. In the second step, I use the model with the two composite climate factors as the template to estimate the GWR relationships. The application of GWR significantly improves the explanatory power of the initial general model. The output from these regressions shows that in regions where it is both excessively hot and dry, these climate attributes are significantly associated with lower LS levels. In contrast, in regions where Climate Factor 1 takes moderately positive values, reflecting benign temperature conditions, it is significantly associated with higher LS levels. Climate Factor 2

representing both wet and warm conditions is not found to be a significant contributor of LS overall, however it is significantly associated with higher LS levels in tropical regions where the climate is both wet and warm. Conversely, in arid and relatively cold regions where Climate Factor 2 takes negative values, it seems to have a significant negative influence on LS.

This study is the first climate focused LS study to apply GWR; it is also the first, to my knowledge, that uses composite climate factors. For these reasons, interpretation of results can be somewhat hazardous. Nonetheless the outcomes are consistent with previous findings from country comparisons that show that higher temperatures in warmer climates have a negative influence on LS (Rehdanz & Maddison, 2005). It also confirms the negative impact of excessive heat on wellbeing that has been documented in several existing studies (Hondula & Barnett, 2014; Nitschke et al., 2011; Zander & Garnett, 2020). This study has subsequently been published in *Weather Climate and Society* (Lignier et al., 2023).

7.2.2 Summary of Chapter 4_ Spatial heterogeneity and subjective wellbeing: exploring the role of social capital in metropolitan areas using multilevel modelling

The objective of this chapter was to address a gap in the literature whereby no study so far had investigated the effects of multiple dimensions of social capital on LS at different levels of interaction in the context of urban neighbourhoods. To fulfill this objective, I design a multi-level modelling approach with nested models at three levels of interaction: individual, household and neighbourhood while controlling for individual socio-demographic factors. I develop successive regression models trying to capture compositional heterogeneity: i.e., how individuals within different neighbourhoods have different characteristics; and contextual heterogeneity: i.e., how different aggregate social capital factors at neighbourhood levels may impact individual LS. I also test for the influence of other contextual variables such as unemployment, income inequality and neighbourhood ethnicity.

The results confirm that social capital factors such as social trust, social engagement and connection and psychological sense of community measured at an individual level contribute positively to LS. Conversely, perceived social dis-amenities such as fear of crime or physical shabbiness in the neighbourhood have a negative impact on LS. Differences in LS levels between neighbourhoods seem to be attributable to compositional effects rather than contextual factors. The influence of contextual social capital appears to be limited to the interaction between individual and aggregate levels of social engagement and connection. In neighbourhoods where aggregate social engagement and connection is high, individual LS

levels are higher, however the impact of *individual* social engagement and connection on LS in such neighbourhoods is reduced. Contrary to the findings of previous research, this study does not find evidence of significant influence for contextual factors such as area unemployment, income inequality and neighbourhood ethnicity. This study has subsequently been accepted for publication in the *Journal of Happiness studies.* At the time of writing, publication is scheduled for the second part of 2024.

7.2.3 Summary of Chapter 5_ How individual perception mitigates the influence of local climate and environment conditions on wellbeing.

The research presented is a preliminary study; its primary objective is to explore the process through which local climate and environment factors influence LS. To this intent, I develop a climate and environment focused conceptual framework based on a neighbourhood focused analytical model used in previous wellbeing research. Using this framework, my enquiry proceeds in several stages. Firstly, I assess the contribution of domain specific satisfaction with the local climate and the local natural environment to overall LS while controlling for demographic factors and other domain satisfaction variables. Secondly, I examine the relationship between subjective perceptions of climate attributes and climate satisfaction as well as the relationship between subjective perceptions of environmental attributes and environment satisfaction. Thirdly, I assess the relationship between subjective climate perceptions and actual climate observations. Finally, I compare the influence of subjective climate perceptions on LS with that of actual climate observations. The analysis is based on multi-stage regression models of survey data.

There are several important outcomes from this exploratory study. Firstly, satisfaction with the local climate and satisfaction with the local environment, two factors often omitted in LS predictive models are both found to be strong positive determinants of LS with coefficients almost as large as health satisfaction and income satisfaction. The second outcome is that subjective perceptions about climate attributes strongly influence the degree of satisfaction with the local climate. The perception that the climate is too hot has a strong negative influence; conversely the perception that the climate is healthy is a key positive contributor. The opinion that the local climate is healthy is itself associated with a perception that the local climate is often sunny and a high frequency of outdoor activities. The third outcome is that the perceived presence of environmental amenities such as beautiful scenery or greenspace is associated with a positive evaluation of the local natural environment, and thus contributes to higher LS levels. The fourth outcome is that subjective perceptions about

climate attributes are more closely associated with variations in LS than actual climate observations. This latter result aligns with previous findings that subjective perceptions about the environment are better predictors of wellbeing than objective indicators (Hur et al., 2010; Kothencz & Blaschke, 2017).

7.2.4 Summary of Chapter 6_ How selective mobility, and social and ecological influence geographic variations in life satisfaction

The objective of this chapter was to explore the reasons behind geographical diversity and geographical clustering of average LS scores. To address this objective, I apply a framework of analysis previously used to explain the spatial diversity and clustering of psychological traits. Under this framework, spatial heterogeneity results from two processes: the influence of selective mobility by which people choose to live in specific areas, and social and ecological influence whereby people's psychological attributes are shaped by the local social and natural environment where they reside. My enquiry is articulated around several research questions relating to the two processes described above. The study considers the following types of selective mobility: moving from an urban area to a rural area, moving from a rural area to an urban area, and moving to a region where the climate is either cooler or warmer It then examines the influence of residing in each of these specific types of environments on individual LS trajectory.

To answer these questions, I used longitudinal data collected over a period of nine years (2013-2021). Logistic regression with random effect estimator is applied to analyse the effect of selective mobility, while linear regression with fixed effect estimator is applied to analyse social influence and ecological influence on individual LS trajectory.

The analysis leads to important findings. In terms of selective mobility, lower LS levels before the move are associated with a higher likelihood to move to a rural area for urban residents, but LS levels have apparently no relationship with a decision to move from a rural area to the city. Lower LS levels before the move are also associated with a higher likelihood to move to a region with a climate that is either warmer or cooler than the original residence. In terms of social and ecological influence, I find that a move from the city to a rural area is associated with an uplift in the individual's LS trajectory; a move from a cool or temperate region to a warmer climate is associated with a similar uplift in LS trajectory. These results align with previous findings on internal migration that a period of stress characterised with lower LS levels precedes migration. This is followed by an uplift in LS levels in the few years that come after the move (Nowok et al., 2013).

7.3 Contributions of this thesis

7.3.1 Contribution to knowledge

The stated research aim of this thesis was to explore the factors that explain the geographic diversity and spatial clustering of LS scores, something that has only received limited attention in the literature. To this intent, I use Australia, a large country with significant diversity in its natural environment and human geography as my field of enquiry. Many of the geographic, cultural, and social characteristics of Australia (described in Chapter 2) are shared with New Zealand, the US and Canada, which means that findings can easily be transferrable to these countries. Some findings may also be relevant to the UK and European countries even though the natural environment and climate are different. The studies in this thesis deliberately adopt a small-scale investigation approach, i.e., contextual variables are defined by reference to a small size neighbourhoods or statistical units comprising 3,000 to 10,000 people: this allows for comparison with LS studies from other countries that have used a similar small scale approach, for example: Helliwell et al. (2019) in Canada; Aminzadeh et al. (2013) in New Zealand; Ballas and Tranmer (2012) in the UK, Weckroth et al. (2022) in Finland.

While the effects of contextual variables such as unemployment, income inequality or the natural environment have been examined previously, the link between these factors and spatial diversity in LS levels has rarely been examined. This thesis also innovates by contrasting the influence of contextual effects on average LS levels with compositional effects, particularly in relation to the influence of social capital. It is also the first study that considers the compositional effects on LS levels related to selective mobility and social influence.

This thesis contributes to the existing body of literature that has examined the influence of the climate on wellbeing, by expanding previous analyses to integrate climate attributes measured in different forms (intensity, duration, average). The use of a single country with an expansive landmass covering several climate zones to conduct this investigation limits the possibility of interference from socio-demographic and cultural differences that may bias the analysis in cross-country comparisons. It also allows the exploration of spatial non-stationarity of LS climate models across regions with different climates (Chapter 3). The exploratory study presented in Chapter 5 provides new insights about the contribution of subjective climate perceptions to wellbeing. It is also the first

research that introduces variables representing a cognitive evaluation of the local climate, and of the local environment, and examines their association with overall LS.

While previous LS research has considered social capital as a contributor, very few studies have investigated the combined influence of different dimensions of social capital on subjective wellbeing and only a handful have examined the interaction of these variables at different levels of influence. The unique contribution of the study presented in Chapter 4 is that it proposes an examination of multiple social capital dimensions using a multilevel approach within a small-scale urban neighbourhood. It also examines the influence of social capital factors in conjunction with other contextual variables such as unemployment, income inequality and neighbourhood ethnicity.

The interaction between wellbeing and international migration has been the object of significant research, however the literature on wellbeing and internal mobility is more limited, particularly in advanced economies. The study in Chapter 6 adds to this burgeoning body of research by examining the interaction between LS and selective mobility; it also contributes to existing research that has investigated spatial clustering in LS scores and other psychological characteristics.

7.3.2 Methodological contribution

Each study in this thesis adopts a specific methodological approach. While these methods may have been applied in LS research before, they had to be adapted for the specific purpose of the research in this thesis.

To my knowledge, geographically weighted regression (GWR) was only used twice in wellbeing research: Kubiszewski, Jarvis, et al. (2019) used this approach to investigate spatial variations of LS in Australia and Jarvis et al. (2017) used it to estimate the value of a specific environment amenity. The focus of the latter study was the environment, not wellbeing; subjective wellbeing was the focus of the first study, however the contributors considered were built, human and social capital, with natural capital represented by a single proxy index. The study in chapter 3 innovates by being the first to apply GWR to the investigation of climate factors.

Multilevel modelling (MLM) has been used as a method of analysis in several wellbeing studies (Ballas & Tranmer, 2012; Neira et al., 2018; Pittau et al., 2010), however the study presented in Chapter 4 is the first where it is applied to the investigation of social capital factors at a small geographic scale in metropolitan areas.

The preliminary study investigating the perception of local climate and local environment (Chapter 5) is groundbreaking even though the small sample size calls for a replication to a larger sample. This study develops a multi-stage regression framework of analysis inspired by a similar framework used in urban wellbeing studies by Mouratidis (2019).

Very few studies have used panel data analysis in LS research with the notable exception of the study by Kubiszewski et al. (2020) on resilience of self-reported LS and the research by Nowok et al. (2013) on LS and residential mobility. The study in Chapter 6 is therefore innovative in exploiting the panel data structure of the HILDA data to undertake a longitudinal analysis of the relationship between selective residential mobility and LS.

7.3.3 Implications for policymaking

Given that the theme of this thesis is to examine the influence of the geographical context on wellbeing, the findings from this research can potentially contribute to various areas of policymaking seeking to improve human wellbeing in specific geographic locations.

The findings about the impact of climate on human wellbeing are particularly relevant in an age where there is a growing interest and concern about the potential effects of climate change on our livelihoods, welfare, and lifestyles. The outcome from the study in Chapter 3 that observed hot temperatures, in particular excessively hot temperatures are associated with lower LS levels for residents, are corroborated by the conclusion from the exploratory study in Chapter 5 that the subjective perception that it is often too hot is negatively associated with LS. These findings will be potentially useful in developing adaptation strategies in the future, particularly in regions with a similar climate to that of Northern Australia where the risk of excessive temperatures is high. The other finding from Chapter 5 that the perception of health and wellbeing benefits from the climate and the environment are important positive contributors of wellbeing opens possibilities of developing policies that will encourage outdoor activities and promote the positive aspects of the local climate and the enjoyment of local environment amenities. The outcome from the study about selective mobility in Chapter 6 has implications for demographers wishing to predict population movements particularly migration to regional areas or to regions with a warmer climate, a phenomenon that was also noticed in previous research in the US (Rappaport, 2007). It may also assist in developing policies that promote living in regional communities or inform policies to assist people who are moving to these areas.

The findings regarding the importance of social capital factors to the wellbeing of residents in metropolitan neighbourhoods (Chapter 4) need to be replicated in studies involving larger metropolitan areas. However, they offer a clear message about promoting social access and social activities within the neighbourhood while remedying against negative perceptions about crime and insecurity. They also emphasise the importance of individual inclusion into the social context as a pathway to improved wellbeing aligning with earlier findings from the study by Wilkinson and Pickett (2009).

7.4 Limitations

Limitations that may hamper the interpretation and reliability of the outcomes reported in this thesis have been acknowledged and discussed in the chapters relating to each specific study. Some of the limitations are linked to the datasets used, others relate to the context of each study and finally some limitations are imposed by the methodological approaches. Here is a summary of these limitations.

The HILDA dataset is used in three of the four studies reported in this thesis. As discussed in Chapter 2, the HILDA surveys are a comprehensive data source of more than 17,000 respondents with annual data collection going as far back as 2001 and as recently as 2021. Its sampling strategy is transparent in its attempts to produce representative samples of the Australian population. However despite its efforts, the HILDA report (Melbourne Institute, 2022) acknowledges that some sections of the population will be under-represented in the sample. This includes people having recently arrived in Australia and people living in remote communities. This sampling bias has potential implications for several of our studies. The under-representation of immigrants and people from non-English speaking backgrounds, may bias the interpretation of results, particularly in the case of the study about social capital in Chapter 4. Similarly, the under-representation of population living in regional and remote rural areas was a limitation while undertaking the GWR investigation. Some statistical units in that study had only a limited number of respondents leading to the possibility that idiosyncratic values of the dependent variable (LS) and some socio-economic factors had a disproportionate influence on averages.

The small sample size and the low response rate to the survey in Chapter 5 is a potential source of bias that may limit external validity and an obstacle to the generalisation of the results from that study. However as argued in Section 5.6.2 in that chapter, the outcomes from this exploratory research offer useful insights into the subjective perception of local climate that may form the basis of a confirmatory study using a larger sample.

Other limitations relate to the context of this research. All studies are situated in Australia, a choice that is justified in Chapter 2, but also motivated by the fact that Australia is my home country. Although Australia has a large area, it has a relatively small population compared to other countries. Australia also has specific attributes, such as a low-density population and a warm climate, the latter characteristic is shared by very few countries with an advanced economy.[84] This may render the generalisation of the findings about climate difficult. There are also context limitations for specific studies, such as the areas targeted by the survey used for the study in Chapter 5 and the use of two specific metropolitan areas (Southeast Queensland and Greater Perth) for the study on social capital in Chapter 4.

Finally, some limitations are imposed by the methodological approach adopted for each study. One such limitation, was the constraint imposed on the analysis by the GWR geographic information system tool, where local multicollinearity prevented the inclusion of certain variables in the model. Throughout the thesis, I have endeavoured to check that the Gauss-Markov assumptions discussed in Chapter 2 were not breached. While some of these assumptions (e.g. multicollinearity or homoskedasticity) could be tested or visually confirmed, others such as that of linearity could not always be tested effectively. All efforts were made to detect possible endogeneity in the models, but it is acknowledged that omitted variables or the presence of reverse causality was an ever-present possibility. In all cases, these limitations are acknowledged for each study.

7.5 Suggestions for future research

Despite the above limitations, the outcomes from the study in this study contribute to knowledge by addressing the research gaps identified in Chapter 1 and provide opportunities for further research.

While addressing Research Gap #1 about the influence of local climate factors on LS, the study presented in Chapter 3 could be replicated in countries with a colder climate, for instance Canada or New Zealand. Excessively high temperatures are unlikely to have as much influence on LS, but other influential factors could emerge.

Research Gap #2 regarding the influence of social capital factors on LS was addressed by the study in Chapter 4. Some of the conclusions from that research were qualified due to the possible sample bias in the data. Also, the influence of contextual factors other than social

[84] The United States is the only advanced economy where some regions share similar climate attributes with Australia.

capital could not be confirmed. It would be beneficial to conduct further research using the same MLM approach in other urban settings to confirm the results from this study. This could involve the inclusion of larger, more multi-cultural metropolitan areas such as Sydney and Melbourne, and or comparison with metropolitan areas in other countries such as Canada and the US.

The study that addressed Research Gap #3 on subjective climate perceptions was exploratory in its design and needs to be replicated by a study using a far larger sample, possibly involving samples from different countries. This would allow to establish links of causality between the different factors The use of modelling techniques such as Structural Equation Modelling may be appropriate for such a confirmatory study.

The study that explores the reasons behind the clustering of LS scores (Research Gap #4) established an association between LS and certain types of selective mobility as well some evidence of social and ecological influence on LS. This relationship needs to be further investigated by research with the aim at establishing causality between variables. This could be done by applying methodologies such as Propensity Score Matching.

References

Abdalah, S., Thompson, S., & Marks, N. (2008). Estimating worldwide life satisfaction. *Ecological Economics, 65*(1), 35-47.

Ahmadiani, M., & Ferreira, S. (2021). Well-being effects of extreme weather eventsin the United States. *Resource and Energy Economics, 64*(101213). doi:https://doi.org/10.1016/j.reseneeco.2020.101213

Ala-Mantila, S., Heinonen, J., Junnila, S., & Saarsalmi, P. (2018). Spatial nature of urban well-being. *Regional Studies, 52*(7), 959-973. doi:https://doi.org/10.1080/00343404.2017.1360485

Alesina, A., Di Tella, R., & MacCulloch, R. (2004). Inequality and happiness: Are Europeans and Americans different? . *Journal of Public Economics, 88*(9), 2009-2042. doi:https://doi:10.1016/j.jpubeco.2003.07.006

Alier, J. M., Pascual, U., Vivien, F.-D., & Zaccai, E. (2010). Sustainable de-growth: Mapping the context, criticisms and future prospects of an emergent paradigm. *Ecological Economics, 69*, 1741-1747. doi:https://doi:10.1016/j.ecolecon.2010.04.017

Ambrey, C., & Fleming, C. (2013). Public Greenspace and Life Satisfaction in Urban Australia. *Urban Studies, 51*(6), 1290-1321.

Ambrey, C., & Fleming, C. (2014). Life Satisfaction in Australia: Evidence from ten years of the HILDA Survey. *Social Indicators Research, 115*, 691-714. doi:https://doi.org/10.1007/s11205-012-0228-0

Ambrey, C., Fleming, C., & Manning, M. (2014). Perception or reality: what matters more when it comes to crime in your neighbourhood. *Social Indicators Research, 119*(2), 877-896.

Aminzadeh, K., Denny, S., Utter, J., Milfont, T., Ameratunga, S., Teevale, T., & Clark, T. (2013). Neighbourhood social capital and adolescent self-reported wellbeing in New Zealand: A multilevel analysis. *Social Science and Medicine, 84*, 13-21. doi:http://dx.doi.org/10.1016/j.socscimed.2013.02.012

Andreasson, U., & Birkjaer, M. (2018). *In the shadow of Happiness*.

Aoshima, I., Uchida, K., Ushimaru, A., & Sato, M. (2018). The influence of subjective perceptions on the valuation of green spaces in Japanese urban areas. *Urban Forestry & Urban Greening, 34*, 166-174. Retrieved from https://doi.org/10.1016/j.ufug.2018.06.018

Asadullah, N., Xiao, S., & Teoh, E. (2018). Subjective wellbeing in China: the role of relative income, gender and location. *China Economic Review, 48*, 83-101.

Aslam, A., & Corrado, L. (2012). The geography of well-being. *Journal of Economic Geography, 12*, 627-649. doi:doi:10.1093/jeg/lbr041

Atkinson, G. (1995). *Measuring sustainable economic welfare A critique of the UK ISEW*. Working Paper. Centre for Social and Economic Research on the Global Environment. Norwich (UK).

Australian Bureau of Statistics. (2016). *Australian Statistical Geography Standard: Volume 1-Main Structure and Greater capital city Statistical Areas, July 2016*. Retrieved from Canberra: https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016?OpenDocument

Australian Bureau of Statistics. (2018). *Socio-Economic Indexes for Areas (SEIFA)-2016*. Retrieved from Canberra: https://www.abs.gov.au/ausstats/abs@.nsf/mf/2033.0.55.001

Australian Bureau of Statistics. (2021-22). Regional Population. Retrieved from https://www.abs.gov.au/statistics/people/population/regional-population/latest-release.

Australian Bureau of Statistics. (2022, 13/12/2022). Australian National Accounts: Distribution of Household Income, Consumption and Wealth. Retrieved from https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-distribution-household-income-consumption-and-wealth/latest-release

Australian Bureau of Statistics. (2023a, 14/9/2023). National, state and territory population: Statistics about the population and components of change (births, deaths, migration) for Australia and its states and territories. March 2023. Retrieved from https://www.abs.gov.au/statistics/people/population/national-state-and-territory-population/latest-release

Australian Bureau of Statistics. (2023b, 9/2/2023). Recorded Crime Offenders: Statistics about offenders proceeded against by police.

Australian Bureau of Statistics. (2023c, 21/03/2023). Remoteness Areas: Australian Statistical Geography Standard (ASGS). Retrieved from https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/remoteness-structure/remoteness-areas

Australian Government. (2021). *National Climate Resilience and Adaptation Strategy*. Retrieved from Canberra: https://www.dcceew.gov.au/climate-change/policy/adaptation/strategy

Ballas, D., & Thanis, I. (2022). Exploring the Geography of Subjective Happiness in Europe During the Years of the Economic Crisis: A Multilevel Modelling Approach. *Social Indicators Research, 164*, 105-137. doi:https://doi.org/10.1007/s11205-021-02874-6

Ballas, D., & Tranmer, M. (2012). Happy People or Happy Places? A Multilevel Modeling Approach to the Analysis of Happiness and Well-Being. *International Regional Science Review, 75*(1), 70-102. doi:10.1177/0160017611403737

Barrington-Leigh, C. (2008). *Weather as a transient influence on survey-reported satisfaction with life*. Department of Economics, University of British Columbia.

Bartram, D. (2011). Economic Migration and Happiness: Comparing Immigrants' and Natives' Happiness Gains from Income. *Social Indicators Research, 107*, 57-76. doi:https://doi.10.1007/s11205-010-9696-2

Bell, S., Phoenix, C., Lovell, R., & Wheeler, B. (2015). Seeking everyday wellbeing: The coast as a therapeutic landscape. *Social Science and Medicine, 142*, 56-67. doi:http://dx.doi.org/10.1016/j.socscimed.2015.08.011

Berlemann, M., & Eurich, M. (2021a). Does drought risk depress expected well-being? *Applied Economics Letters, 29*(13), 1229-1233. doi:https://doi.org/10.1080/13504851.2021.1922582

Berlemann, M., & Eurich, M. (2021b). Natural hazard risk and life satisfaction- Empirical evidence for hurricanes. *Ecological Economics, 190*(107194). doi:https://doi.org/10.1016/j.ecolecon.2021.107194

Bertram, C., & Rehdanz, K. (2015). The role of urban green space for human well-being. *Ecological Economics, 120*, 139-152. doi:https://doi:10.1016/j.ecolecon.2015.10.013

Biedenweg, K., Scott, R., & Scott, T. (2017). How does engaging with nature relate to life satisfaction? Demonstrating the link between environment specific social experiences and life satisfaction. *Journal of Environmental Psychology, 50*, 112-124.

Blanchflower, D., & Oswald, A. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics, 88*, 1359-1386.

Blanchflower, D., & Oswald, A. (2011). International Happiness: A New View on the Measure of Performance. *Academy of Management Perspectives, 25*(1), 6-22.

Blanton, H., & Jaccard, J. (2006). Arbitrary Metrics in Psychology. *American Psychologist, 61*(1), 27-41. doi:10.1037/0003-066X.61.1.27

Bleys, B. (2012). Beyond GDP: Classifying Alternative Measures for Progress. *Social Indicators Research, 109*, 355-376.

Boes, S., & Winkelmann, R. (2010). The Effect of Income on General Life Satisfaction and Dissatisfaction. *Social Indicators Research, 95*, 111-128. doi:10.1007/s11205-009-9452-7

Bond, R., Fariss, C., Jones, J., Kramer, A., Marlow, C., Settle, J., & Fowler, J. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature, 489*(295), 296-298. doi:http://doi:10.1038/nature11421

Bonini, A. (2008). Cross-national Variations in Indiviudual Life Satisfaction: Effects of National Wealth, Human Development and Environmental Conditions. *Social Indicators Research, 87*, 223-236. doi:10.1007/s11205-007-9167-6

Brereton, F., Clinch, J. P., & Ferreira, S. (2008). Happiness, geography and the environment. *Ecological Economics, 65*, 386-396. doi:https://doi.org/10.1016/j.ecolecon.2007.07.008

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Hetroskedasticity and Random Coefficient Variation. *Econometrica, 27*(5), 1287-1294. doi:https://doi:10.2307/1911963

Brooks, A., Ottley, K., Arbuthnott, K., & Sevigny, P. (2017). Nature-related mood effects: Season and the type of nature contact. *Journal of Environmental Psychology, 54*, 91-102.

Bruna, F. (2021). Happy cultures? A Multilevel Model of Well-being with Individual and Contextual Human Values. *Social Indicators Research, 164*, 55-77. doi:https://doi.org/10.1007/s11205-021-02858-6

Bruni, L. (2006). *Civil happiness. Economics and Human Flourishing in Historical Perspective.* doi:https://doi.org/10.4324/9780203488119

Bureau of Meteorology. (2005). Climate classification of Australia. Retrieved from http://www.bom.gov.au/climate/maps/averages/climate-classification/?maptype=kpngrp

Bureau of Meteorology (Cartographer). (2006). Climate Classification maps: Temperature/humidity zones. Retrieved from http://www.bom.gov.au/climate/maps/averages/climate-classification/?maptype=tmp_zones

Bureau of Meteorology. (2010). Australia Climate Influences. Retrieved from http://www.bom.gov.au/climate/about/australian-climate-influences.shtml

Bureau of Meteorology. (2013). Climate Data online. Retrieved from http://www.bom.gov.au/climate/data/

Bureau of Meteorology. (2021). NDVI Average for Australia. Retrieved from http://www.bom.gov.au/jsp/awap/ndvi/index.jsp

Bureau of Meteorology (Producer). (2022, 20/9/2022). Average daily solar exposure. [Map] Retrieved from http://www.bom.gov.au/jsp/ncc/climate_averages/solar-exposure/index.jsp

Bureau of Meteorology. (2023). Tropical Cyclone Reports. Retrieved from http://www.bom.gov.au/cyclone/tropical-cyclone-knowledge-centre/history/past-tropical-cyclones/

Butikofer, A., & Peri, G. (2017). *The Effects of Cognitive and Noncognitive Skills on Migration Decisions*. (ISSN: 0804-6824).

Calvo, R., Arcaya, M., Baum, C., Lowe, S., & Waters, M. (2015). Happily Ever After? Pre-and-Post Disaster Determinants of Happiness Among Survivors of Hurricane Katrina. *Journal of Happiness Studies, 16*, 427-442. doi:https://doi.org/10.1007/s10902-014-9516-5

Cameron, A. C., & Trivedi, P. K. (2010). *Miroeconometrics Using Stata* (Revised ed.): Stata Press.

Campbell, P. (2019). Dispositional traits and internal migration: Personality as a predictor of migration in Australia. *Journal of Research in Personality, 78*, 262-267. doi:https://doi.org/10.1016/j.jrp.2018.12.009

Cantril, H. (1965). *The Pattern of Human Concerns*. New Brunswick, NJ: Rutgers University Press.

Caroll, N., Frijters, P., & Shields, M. (2009). Quantifying the costs of drought: new evidence from the life satisfaction data. *Journal of Population Economics, 22*, 445-461. doi:https://doi.org/10.1007/s00148-007-0174-3

Castorina, D., & Welters, R. (2022). Interregional Migration: Who Decides to Move? *Bulletin ofApplied Economics, 9*(1), 97-114. doi:https://doi.org/10.47260/bae/917

Chaiechi, T. (Ed.) (2020). *Economic Effects of Natural Disasters: Theoretical Foundations, Methods and Tools*: Academic Press.

Chaiechi, T., & Tavares, S. (2019). Urban growth, heat islans, humidity, climate chane: the costs multiply in tropical cities. *The Conversation*. Retrieved from https://theconversation.com/urban-growth-heat-islands-humidity-climate-change-the-costs-multiply-in-tropical-cities-120825

Chen, L., & Ng, E. (2012). Otdoor thermal comfort and outdoor activities: a review of the research in the past decade. *Cities, 29*, 118-125. doi:https://doi:10.1016/j.cities.2011.08.006

Clark, A. (2003). Unemployment as a Social Norm: Psychological Evidence from Panel Data. *Journal of Labor Economics, 21*(2), 323-351.

Clark, A., Frijters, P., & Shields, M. (2008). Relative Income, Happiness and Utility: An explanation of the Easterlin Paradox and other Puzzles. *Journal of Economic Theory, 46*(1), 95-144.

Clark, A., & Oswald, A. (1994). Unhappiness and Unemployment. *The Economic Journal, 104*(424), 648-659.

Cohen, D. (1996). Law, Social Policy and Violence: The Impact of Regional Cultures. *Journal of Personality and social psychology, 70*(5), 961-978.

Coleman, J. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology, 94*, S95- S120. Retrieved from https://www.jstor.org/stable/2780243

Connolly, M. (2013). Some like it hot and not too wet: the influence weather on subjective well-being. *Journal of Happiness Studies, 14*(2), 457-473. doi:https://doi.org/10.1007/s10902-012-9338-2

Costa, P., & McCrae, R. (1980). Influence of Extraversion and Neuroticism on Subjective Well-Being: Happy and Unhappy People. *Journal of Personality and social psychology, 38*(4), 668-678.

Costa, P., & McCrae, R. (1992). Normal Personality Assessment in Clinical Practice: The NEO Personality Inventory. *Psychological Assessment, 4*(1), 5-13.

Costa, P., & McCrae, R. (1998). Trait Theories of Personality. In D. F. Barone, M. Hersen, & V. B. Van Hasselt (Eds.), *Advanced Personality. The Plenum Series in Social/Clinical Psychology.* Boston, MA: Springer.

Costanza, R., Alperowitz, G., Daly, H., Farley, J., Franco, C., Jackson, T., . . . Victor, P. (2013). *Building a Sustainable and Desirable Economy-In-Society-In -Nature*. Canberra: ANU Press.

Costanza, R., Hart, M., Posner, S. M., & C.J., T. (2009). *Beyond GDP:The Need for New Measures of Progress*. The Pardee Papers, (4). Boston.

Couper, M. (2011). The future modes of data collection. *Public Opion Quarterly, 75*(5), 889-908.

Cramer, V., Torgesen, S., & Kringlen, E. (2004). Quality of life in a city: The effect of population density. . *Social Indicators Research, 69*(1), 103-116. doi:https://doi:10.1023/B:SOCI.0000032663.59079.0b

Creswell, J. W. (1994). *Research design: quantitative and qualitative approaches*. Thousand Oaks, California: Sage Publications.

Cummins, R. (1996). The Domains of Life Satisfaction: An Attempt to Order Chaos. *Social Indicators Research, 38*, 303-328.

Cummins, R. (2000). Objective and subjective quality of life: an interactive model. *Social Indicators Research, 52*, 55-72. doi:https://doi.org/10.1023/A:1007027822521

Cummins, R. (2018). Subjective Wellbeing as Social Indicator. *Social Indicators Research, 135*, 879-891. doi:https://doi.org/10.1007/s11205-016-1496-x

Cummins, R., Eckersley, R., Pallant, J., Van Vugt, J., & Misajon, R. (2003). Developing a national index of subjective wellbeing: the Australian Unity Wellbeing. *Social Indicators Research, 64*, 159-190.

Cushing, B. (1987). A note on specifications of climate variables in models of population migration. *Journal of Regional Science, 27*(4), 641-649. doi:https://doi.org/10.1111/j.1467-9787.1987.tb01186.x

Daly, H. (1987). The Economic Growth Debate: What Some Economists Have Learned But Many Have Not. *Journal of Environmental Economics and Management, 14*.

Daly, H. (2014). *From Uneconomic Growth to a Steady-State Economy*. Cheltenham, UK: Edward Edgar Publishing.

Daly, H., & Cobb, J. (1989). *For the Common Good*. Boston: Beacon Press.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting & Social Change, 173*(121092). doi:https://doi.org/10.1016/j.techfore.2021.121092

Davidson, R., & McKinnon, J. (1993). *Estimation and inference in econometrics*: Oxford University Press.

de Leeuw, J., & Meijer, E. (Eds.). (2008). *Introduction to Multilevel Analysis*. Berlin: Springer.

de Vries, S., Verhij, R., Groenewegen, P., & Spreuwenberg, P. (2003). Natural Environments—Healthy Environments? An Exploratory Analysis of the Relationship between Greenspace and Health *Environment and Planning A: Economy and space, 35*(10), 1717-1731. doi:https://doi.org/10.1068/a35111

Deci, E., & Ryan, R. (2008). Hedonia, eudaimonia, and wellbeing: an introduction. *Journal of Happiness Studies, 9*, 1-11. doi:10.1007/s10902-006-9018-1

Diener, E. (2006). Guidelines for National Indicators of Subjective Well-Being and Ill-Being. *Applied Research in Quality of Life, 1*, 151-157. doi:http://dx.doi.org/10.1007/s11482-006-9007-x

Diener, E., & Lucas, R. E. (1999). Personality and subjective wellbeing. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Wellbeing: the foundation of hedonic psychology.* New York: Russell Sage Foundation.

Diener, E., & Oishi, S. (2000). Money and happiness: income and subjective wellbeing across nations. In E. Diener & E. Suh (Eds.), *Subjective wellbeing across cultures.* Cambridge (Mass): MIT Press.

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective Well-being research. *Nature human behaviour, 2*, 253-260. doi:10.1038/s41562-018-0307-6

Diener, E., & Suh, E. (1997). Measuring quality of life: economic, social and subjective indicators. *Social Indicators Research, 40*, 189-216.

Diener, E., Suh, E., Lucas, R. E., & Smith, H. L. (1999). Subjective Well-being: Three Decades of Progress. *Psychological Bulletin, 125*(2), 1276-1302.

Dillman, D., Smyth, J., & Christian, L. M. (2014). *Internet, Phone, mail and Mixed Mode Surveys: the Taylored Design Method* (4th ed.). Hoboken, NJ: John Wiley and Sons.

Duncan, C., Jone, K., & Moon, G. (1998). Context, composition and heterogeneity: Using multilevel models in health research. *Social Science and Medicine, 46*(1), 97-117.

Dziak, J. J., Dierker, L., & Abar, B. (2020). The interpretation of statistical power after the data has been gathered. *Current Psychology, 39*, 870-877. doi:https://doi.org/10.1007/s12144-018-0018-1

Easterlin, R. (1974). Does Economic Growth Improve the Human Lot? In P. David & M. Reder (Eds.), *Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz*. New York: Academic Press.

Easterlin, R. (1995). Will rasing the incomes of all increase the happiness of all? *Journal of Economic Behavior and Organization, 27*, 35-47.

Easterlin, R. (2003). Explaining Happiness. *Proceedings of the National Academy of Sciences, 100*(19), 11176-11183.

Easterlin, R., McVey, L., Switek, M., Sawangfa, O., & Smith Zweig, J. (2010). The Happiness-Income Paradox revisited. *Proceedings of the National Academy of Sciences of the United States of America, 107*(52), 22463-22468.

Eckersley, R. (2000). The state and fate of nations: implication of subjective measures of personal and social quality of life. *Social Indicators Research, 52*, 3-27.

Emmons, R., & Diener, E. (1986). An interactional approach to the study of personality and emotion. *Journal of Personality, 54*, 375-384.

Engelbrecht, H. J. (2009). Natural capital, subjective wellbeing and the new welfare economics of sustainability: Some evidence from cross-country regressions. *Ecological Economics, 69*, 380-388.

Ettema, D., & Schekkerman, M. (2016). How do spatial characteristics influence well-being and mental health? Comparing the effect of objective and subjective characteristics at different spatial scales. *Travel Behaviour and Society, 5*, 56-67. doi:http://dx.doi.org/10.1016/j.tbs.2015.11.001

Fastame, M. C., Ruiu, M., & Mulas, I. (2022). Hedonic and Eudaimonic well-being in late adulthood: Lessons from Sardinia's Blue Zone. *Journal of Happiness Studies, 23*, 713-726. doi:https://doi.org/10.1007/s10902-021-00420-2

Feddersen, J., Metcalfe, R., & Wooden, M. (2016). Subjective wellbeing: why weather matters. *Journal of The Royal Statistical Society (Series A: Statistics in Society), 179*(1), 203-228. doi:https://doi.org/10.1111/rssa.12118

Fernandez, C. J., Stoeckl, N., & Welters, R. (2019). The cost of doing nothing in the face of climate change: a case study, using the life satisfaction approach to value the tangible and intangible costs of flooding in the Philippines. *Climate and Development, 11*(9), 825-838. doi: https://doi.org/10.1080/17565529.2019.1579697

Fernandez, R., & Kulik, J. (1981). A Multilevel Model of Life Satisfaction: Effects of Individual Characteristics and Neighborhood Composition. *American Sociological Review, 46*(6), 840-850. Retrieved from https://www.jstor.org/stable/2095082

Ferreira, S., Akay, A., Brereton, F., Cunado, J., Martinsson, P., Moro, M., & Ningal, T. (2013). Life Satisfaction and Air Quality in Europe. *Ecological Economics, 88*, 1-10. doi:https://doi.org/10.1016/j.ecolecon.2012.12.027

Ferreira, S., & Moro, M. (2010). On the Use of Subjective Well-Being Data for Environmental Valuation. *Environmental Resource Economics, 46*, 249-273.

Ferreira, S., & Moro, M. (2013). Income and preferences for the environment: evidence from the subjective wellbeing data. *Environment and Planning, 45*, 650-667. doi:10.1068/a4540

Ferrer-i-Carbonell, A. (2013). Happiness Economics. *SERIEs, 4*, 35-60. doi:https://doi.org/10.1007/s13209-012-0086-7

Ferrer-i-Carbonell, A., & Frijters, P. (2004). How important is methodology for the estimates of determinants of happiness. *The Economic Journal, 114*, 641-659.

Ferrer-i-Carbonell, A., & Gowdy, J. (2007). Environmental degradation and happiness. *Ecological Economics, 60*, 509-516.

Fishburn, P. (1968). Utility Theory. *Management Science, 14*(5), 335-378.

Florida, R. (2009). *Who's your City? How the Creative Economy is Making Where to Live the Most Important Decision of your Life.* New York: Basic Books.

Florida, R., & Mellander, C. (2010). There goes the metro: how and why bohemians, artists and gays affect regional housing values. *Journal of Economic Geography, 10*(2), 167-188. doi:https://doi.org/10.1093/jeg/lbp022

Florida, R., & Mellander, C. (2016). The Geography of Inequality: Difference and Determinants of Wage and Income Inequality across US Metros. *Regional Studies, 50*(1), 79-92. doi:https://doi.org/10.1080/00343404.2014.884275

Florida, R., Mellander, C., & Rentfrow, P. (2013). The happiness of Cities. *Regional Studies, 47*, 613-627. doi:https://doi.org/10.1080/00343404.2011.589830

Fotheringham, A., Brunsdon, C., & Charlton, S. (2002). *Geographically weighted regression: the analysis of spatially varying relationships*. West Sussex: John Wiley and Sons.

Fotheringham, A., & Oshan, T. (2017). Geographically weighted regression and multicollinearity: dispelling the myth. *Journal of Geographical Systems, 18*, 303-329. doi:https://doi.org/10.1007/s10109-016-0239-5

Frey, B. (2018). *Economics of happiness*. doi:https://doi.org/10.1007/978-3-319-75807-7

Frey, B., & Gallus, J. (2013a). Political economy of happiness. *Applied Economics, 45*(30), 4205-4211. doi:/10.1080/00036846.2013.778950

Frey, B., & Gallus, J. (2013b). Subjective Well-being and Policy. *Topoi, 32*, 207-212. doi:10.1007/s11245-013-9155-1

Frey, B., & Stutzer, A. (2000). Happiness, Economy and Institutions. *The Economic Journal, 110*, 918-938.

Frey, B., & Stutzer, A. (2012). The use of happiness research for public policy. *Social Choice and Welfare, 38*, 659-674. doi:https://doi.org/10.1007/s00355-011-0629-z

Frijters, P., & Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior and Organization, 82*, 525-542. doi:https://doi.org/10.1016/j.jebo.2012.03.008

Frijters, P., Lalji, C., & Pakrashi, D. (2020). Daily weather only has small effects on wellbeing in the US. *Journal of Economic Behavior and Organization, 176*, 747-762. doi:https://doi.org/10.1016/j.jebo.2020.03.009

Frijters, P., & Van Praag, B. (1998). The effects of climate on welfare and well-being in Russia. *Climatic Change, 39*, 61-81.

Gasper, D. (2004). *Human wellbeing: concepts and conceptualization*. Discussion Paper No 2004/6. Helsinki.

GaWC. (2020). The World according to GaWC 2020. Retrieved from https://www.lboro.ac.uk/microsites/geography/gawc/world2020t.html

Gelman, A., & Hill, J. (2007). *Data Analysis using Regression an Nultilevel/ Hierarchical Models*.

Gilbert, A., Colley, K., & Roberts, D. (2016). Are rural residents happier? A quantitative analysis of subjective wellbeing in Scotland. *Journal of Rural Studies, 44*, 37-45. doi:http://dx.doi.org/10.1016/j.jrurstud.2016.01.002

Glaeser, E., Gottlieb, J. D., & Ziv, O. (2016). Unhappy cities. *Journal of Labor Economics, 34*(S2). doi:http://doi:10.1086/684044

Graham, C., & Nikolova, M. (2015). Bentham or Aristotle in the Development Process? An Empirical Investigation of Capabilities and Subjective Well-Being. *World Development, 68*, 168-179. doi:http://dx.doi.org/10.1016/j.worlddev.2014.11.018

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. *Proceedings of the National Academy of Sciences, 109*(37), E2415- E2423. doi:https://doi.org/10.1073/pnas.1205276109

Harter, J., Stampone, M., Ryan, S., Kirner, K., Chapman, C., & Goldman, A. (2012). Patterns and Perceptions of Climate Change in a Biodiversity Conservation Hotspot. *Plos one, 7*(2), e32408. doi:https://doi.org/10.1371/journal.pone.0032408

Helliwell, J. (2003). How's life? Combining individual and national variables to explain subjective wellbeing. *Economic Modelling, 20*, 331-360.

Helliwell, J., & Barrington-Leigh, C. (2010). Viewpoint: Measuring and understanding subjective wellbeing. *Canadian Journal of Economics, 43*(3), 729-753. doi:https://doi.org/10.1111/j.1540-5982.2010.01592.x

Helliwell, J., & Putnam, R. (2004). *The social context of wellbeing.* Philosophical Transactions, (359, 1449). London.

Helliwell, J., Shiplett, H., & Barrington-Leigh, C. (2019). How happy are your neighbours? Variation in life satisfaction among 1200 Canadian neighbourhoods and communities. *Plos one, 14*(e210091). doi:https://doi.org/10.1371/journal.pone.0210091

Hendriks, M., & Bartram, D. (2018). Bringing Happiness into the Study of Migration and its Consequences: What, Why and How? *Journal of Immigrant & Refugee Studies, 17*(3), 279-298. doi:https://doi.org/10.1080/15562948.2018.1458169

Hitchings, R. (2011). Coping with the immediate experience of climate: regional variations and indoor trajectories. *WIREs Climate change, 2*, 170-184. doi:https://doi.org/10.1002/wcc.106

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations.* (2nd ed.). Thousand Oaks, CA: Sage.

Hofstede, G., & McCrae, R. (2004). Personality and Culture Revisited: Linking Traits and Dimensions of Culture. *Cross-Cultural Research, 38*(1). doi:https://doi.org/10.1177/10693971032594

Hondula, D. M., & Barnett, A. (2014). Heat-related morbidity in Brisbane, Australia: spatial variation and area-level predictors. *Environmental Health Perspectives, 122*, 831-836. doi:http://dx.doi.org/10.1289/ehp.1307496

Howe, P., & Leiserowitz, A. (2013). Who remembers a hot summer or a cold winter? The asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the U.S. *Global Environmental Change, 23*, 1488-1500. doi:http://dx.doi.org/10.1016/j.gloenvcha.2013.09.014

Howell, A., Dopko, R., Passmore, H. A., & Buro, K. (2011). Nature connectedness: Association with wellbeing and mindfulness. *Personality and Individual Differences, 51*(166-71).

Hox, J. (Ed.) (1998). *Multilevel Modelling: When and Why.* Berlin: Springer.

Hsieh, C. M. (2012). Importance is Not Unimportant:: The Role of Importance Weighting in QOL Measures. *Social Indicators Research, 109*, 267-278.

Hulme, M., Dessai, S., Lorenzoni, I., & Nelson, D. (2009). Unstable climates: Exploring the statistical and social constructions of 'normal' climate. *Geoform, 40*, 197-206. doi:https://doi:10.1016/j.geoforum.2008.09.010

Hummel, D. (2016). Inter-State Internal Migration: State Level Wellbeing as a Cause. *Journal of Happiness Studies, 17*, 2149-2165. doi:https://doi.10.1007/s10902-015-9689-6

Hur, M., Nasar, J. L., & Chun, B. (2010). Neighborhood satisfaction, physical and perceived naturalness and openness. *Journal of Environmental Psychology, 30*(1), 52-59. doi:http://doi:10.1016/j.jenvp.2009.05.005

Huta, V., & Ryan, R. (2010). Pursuing pleasure or virtue: the differential and overlapping well-being benefits of hedonic and audaimonic motives. *Journal of Happiness Studies, 11*, 735-762. doi:https://doi.org/10.1007/s10902-009-9171-4

Inglehardt, R. (1990). *Culture shift in advanced industrial society*. Princeton, NJ: Princeton University Press.

Inglehardt, R., Foa, R., Peterson, C., & Welzel, C. (2008). Development, Freedon, and Rising Happiness. A global Perspective (1981-2007). *Perspectives on Psychological Science, 3*(4).

Inglehardt, R., & Klingemann, H. D. (2000). Genes, culture, democracy and happiness. In E. Diener & E. Suh (Eds.), *Subjective wellbeing across cultures.* Cambridge (Mass): MIT Press.

IPCC. (2022). *Sixth assessment Report: Impacts, adaptation and vulnerabilities. Chapter 11: Australasia*. Retrieved from https://www.ipcc.ch/report/ar6/wg2/

Jarvis, D., Lignier, P., Kubiszewski, I., & Costanza, R. (2023). Natural Capital, Ecosystem Services and Subjective Wellbeing: a Systematic Review. In E. Rieger, R. Costanza, I. Kubiszewski, & P. Dugdale (Eds.), *Toward An Integrated Science of Wellbeing.* Oxford (UK): Oxford University Press.

Jarvis, D., Stoeckl, N., & Liu, H. (2017). New methods for valuing, and for identifying spatial variations, in cultural services: a case study of the Great Barrier Reef. *Ecosystem Services, 24*, 58-67. doi:http://dx.doi.org/10.1016/j.ecoser.2017.02.012

Jebb, A., Tay, L., Diener, E., & Oishi, S. (2018). Happiness, income satisfaction and turning points around the world. *Nature human behaviour, 2*, 33-38. doi:https://doi.org/10.1038/s41562-017-0277-0

Johnson, R. A., & Wichern, D. W. (2002). *Applied Multivariate Statistical Analysis* (5th ed.): Pearson.

Jokela, M. (2009). Persomality predicts migration between and within US states. *Journal of Research in Personality, 43*, 79-83. doi:http://doi:10.1016/j.jrp.2008.09.005

Jokela, M. (2014). Personality and the realization of migration desires. In P. Rentfow (Ed.), *Geographical psychology: Exploring the interaction of environment and behavior.* (pp. 81-97): American Psychological Asociation.

Jokela, M. (2020). Selective residential mobility and social influence in the emergence of neighborhood personality differences: Longitudinal data from Australia. *Journal of Research in Personality, 86*(103953). doi:https://doi.org/10.1016/j.jrp.2020.103953

Jokela, M. (2021). Personality traits and reasons for residential mobility: Longitudinal data from United Kingdom, Germany, and Australia. *Personality and Individual Differences, 180*(110978). doi:https://doi.org/10.1016/j.paid.2021.110978

Jokela, M., Bleidorn, W., Lamb, M., Gosling, S., & Rentfrow, P. (2015). Geographically varying associations between personality and life satisfaction in the London metropolitan area. *PNAS, 112*(3), 725-730. Retrieved from www.pnas.org/cgi/doi/10.1073/pnas.1415800112

Jokela, M., Elovainio, M., Kivimaki, M., & Keltikangas-Jarvinen, L. (2008). Temperament and Migration Patterns in Finland. *Psychological Science, 19*(9), 831-837. doi:https://doi.org/10.1111/j.1467-9280.2008.02164.x.

Kahan, D. (2013). Ideology, motivated reasoning, and cognitive reflection. *Judgment and Decision Making, 8*(4), 407-424.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences, 107*(38), 16489 - 16493. doi:https://doi.org/10.1073/pnas.1011492107

Kahneman, D., Diener, E., & Schwarz, N. (1999). *Wellbeing: Foundations of hedonic psychology*.

Kahneman, D., & Krueger, A. (2006). Developments in the Measurement of Subjective Well-Being. *Journal of Economic Perspectives, 20*(1), 3-24.

Kahneman, D., Krueger, A., Schkade, D., Schwarz, N., & Stone, A. (2004). Toward National Well-Being Accounts. *American Economic Review, 94*(2), 429-434.

Kahneman, D., Wakker, P., & Sarin, R. (1997). Back to Bentham? Exploration of experienced utility. *Quarterly Journal of Economics, 112*(2), 375-406. doi:10.1162/003355397555235

Katzner, D. (1998). The misuse of measurement in economics. *Metroeconomica, 49*(1), 1-22.

Keller, M., Frederickson, B., Ybarra, O., Cote, S., Johnson, K., Mickel, J., . . . Wager, T. (2005). A Warm Heart and a Clear Head. The Contingent Effects of Weather on Mood and Cognition. *Psychological Science, 16*(9), 714-731. doi:https://doi.org/10.1111/j.1467-9280.2005.01602.x

Killingsworth, M. (2021). Experienced well-being rises with income, even above $75,000 per year. *Proceedings of the National Academy of Sciences, 118*(4), 1-6. doi:https://doi.org/10.1073/pnas.2016976118

Koenker, R. (1981). A note on studentizing a test for heteroskedasticity. *Journal of Econometrics, 17*, 107-112. doi:https://doi.org/10.1016/0304-4076(81)90062-2

Kothencz, G., & Blaschke, T. (2017). Urban parks: Visitors' perceptions versus spatial indicators. *Land Use Policy, 64*, 233-244. Retrieved from http://dx.doi.org/10.1016/j.landusepol.2017.02.012

Kovats, R. S., & Hajat, S. (2008). Heat Stress and Public Health: A Critical Review. *Annual Review of Public Health, 29*, 41-55. doi:10.1146/annurev.publhealth.29.020907.090843

Kraehnert, K., & Fluhrer, S. (2021). *Sitting in the same boat: Subjective well-being and social comparison after an extreme weather event*. Paper presented at the Beiträge zur Jahrestagung des Vereins für Socialpolitik 2021, Kiel (Germany).

Kristoffersen, I. (2010). The Metrics of Subjective Wellbeing: Cardinality, Neutrality and Additivity. *The Economic Record, 86*(272), 98-123. doi:https://doi.org/10.1111/j.1475-4932.2009.00598.x

Kristoffersen, I. (2017). The Metrics of Subjective Wellbeing Data:An empirical Evaluation of the Ordinal and Cardinal Comparability of Life Satisfaction Scores. *Social Indicators Research, 130*, 845-865. doi:https://doi.org/10.1007/s11205-015-1200-6

Krueger, A., & Schkade, D. (2008). The reliability of subjective well-being measures. *Journal of Public Economics, 92*, 1833-1845.

Kubiszewski, I., Costanza, R., Franco, C., Lawn, P., Talberth, J., Jackson, T., & Aylmer, C. (2013). Beyond GDP: Measuring and achieving global genuine progress. *Ecological Economics, 93*, 57-68.

Kubiszewski, I., Jarvis, D., & Zakariyya, N. (2019). Spatial variations in contributors to life satisfaction: An Australian case study. *Ecological Economics, 164*, 1-10. doi:https://doi.org/10.1016/j.ecolecon.2019.05.025

Kubiszewski, I., Zakariyya, N., & Costanza, R. (2018). Objective and Subjective Indicators of Life Satisfaction in Australia: How Well Do People Perceive What Supports a Good Life? *Ecological Economics, 154*, 361-372. doi:https://doi.org/10.1016/j.ecolecon.2018.08.017

Kubiszewski, I., Zakariyya, N., Costanza, R., & Jarvis, D. (2020). Resilience of self-reported life satisfaction: A case study of who conforms to set-point theory in Australia. *Plos one*, 1-18. doi: https://doi.org/10.1371/journal.pone.023716

Kubiszewski, I., Zakariyya, N., & Jarvis, D. (2019). Subjective wellbeing at different spatial scales for individual satisfied and dissatisfied with life *Peer J, 7*, 1-25. doi:https://peerj.com/articles/6502/

(2013). *A full course in econometrics- undergraduate level- Part 1* [

Lankford, S., Buxton, B., Hetzler, R., & Little, J. (1995). Response Bias and Wave Analysis of Mailed Questionnaires in Tourism Impact Assessments. *Journal of Travel Research, Spring*, 8-13.

Larsen, R., & Ketelaar, T. (1991). Personality and suceptibility to positive and negative emotional states. *Journal of Personality and social psychology, 61*, 132-140.

Larson, S. (2009). Communicating Stakeholders Priorities in the Great Barrier Reef Region. *Society and Natural Resources, 22*, 650-664.

Larson, S. (2010). Regional wellbeing in tropical Queensland, Australia: developping a dissatisfaction index to inform government policy. *Environment and Planning, 42*, 2972-2989.

Larson, S., Stoeckl, N., Jarvis, D., Addison, J., Grainger, D., Watkin Liu, F., & Walalakoo Aboriginal Corporation, B. D. A. C. R., Ewamian Aboriginal Corporation RNTBC, Yununijarra Aboriginal Corporation RNTBC. (2020). Indigenous Land and Sea Management Programs (ILSMPs) Enhance the Wellbeing of Indigenous Australians. *International Journal of Environmental Research and Public Health, 17*.

Larson, S., Stoeckl, N., Jarvis, D., Addison, J., Prior, S., & Esparon, M. (2019). Using measures of wellbeing for impact evaluation: Proof of concept developed with an Indigenous community undertaking land management programs in northern Australia. *Ambio, 48*, 89-98. doi:10.1007/s13280-018-1058-3

Lawless, N., & Lucas, B. (2010). Predictors of regional well-being: a county level analysis. *Social Indicators Research, 101*(3), 341-357. doi:https://doi.10.1007/sl.1205-010-9667-7

Layard, R. (2005). *Happiness: lessons from a new science*. London: Allen Lane.

Lee, E. S. (1966). A Theory of Migration. *3*(1), 47-57. Retrieved from http://www.jstor.org/stable/2060063

Levinson, A. (2009). *Valuing public goods using happiness data: the case of air quality*. WP 15156. Cambridge MA.

Li, N. P., & Kanazawa, S. (2016). Country roads, take me home. . . to my friends: How intelligence, population density, and friendship affect modern happiness. *British Journal of Psychology, 107*, 675-697. doi:https://DOI:10.1111/bjop.12181

Li, Q., Stoeckl, N., King, D., & Guyris, E. (2018). Using both Objective and Subjective Indicators to Investigate the Impact of Coal Mining on Wellbeing of Host Communities: A case Study in Shan Xi Province in China. *Social Indicators Research, 137*, 895-921.

Liao, P. S., Shaw, D., & Lin, Y. M. (2015). Environmental Quality and Life Satisfaction: Subjective Versus Objective Measures of Air Quality. *Social Indicators Research, 124*(2), 599-616. doi:http://10.1007/s11205-014-0799-z

Lignier, P., Jarvis, D., Grainger, D., & Chaiechi, T. (2023). Does the Climate Impact Satisfaction with Life? An Australian Spatial Study. *Weather, Climate, and Society, 15*(1), 159-175. doi:https://doi.org/10.1175/WCAS-D-22-0063.1

Lindner-Cendrowska, K., & Blazejczyk, K. (2018). Impact of selected personal factors on seasonal variability of recreationist weather perceptions and preferences in Warsaw (Poland). *International Journal of Biometeorology, 62*, 113-125. doi:https://doi.org/10.1007/s00484-016-1220-1

Lucas, R. E., & Lawless, N. (2013). Does life seem better on a sunny day: Examining the association between daily weather conditions and life satisfaction judgements. *Journal of Personality and social psychology, 104*(2), 872-884. doi:https://doi.org/10.1037/a0032124

Luechinger, S. (2009). Valuing Air Quality Using the Life Satisfaction Approach. *The Economic Journal, 119*, 482-515.

Luechinger, S., & Raschky, P. (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics, 93*, 620-633. doi:doi:10.1016/j.jpubeco.2008.10.003

Lykken, D., & Tellegen, A. (1996). Happiness is a stochastic phenomenon. *Psychological Science, 7*, 186-189.

Lynn, M., & Steel, P. (2006). National Differences in Subjective Well-being: the Interactive Effects of Extraversion and Neuroticism. *Journal of Happiness Studies, 7*, 155-165. doi:http://DOI10.1007/s10902-005-1917-z

Ma, J., Dong, G., Chen, Y., & Zhang, W. (2018). Does satisfactory neighbourhood environment lead to a satisfying life? An investigation of the association between neighbourhood environment and life satisfaction in Beijing. *Cities, 74*, 229-239. doi:https://doi.org/10.1016/j.cities.2017.12.008

MacKerron, G., & Mourato, S. (2009). Life satisfaction and air quality in London. *Ecological Economics, 68*, 1441-1453. doi::10.1016/j.ecolecon.2008.10.004

MacKerron, G., & Mourato, S. (2013). Happiness is greater in natural environments. *Global Environmental Change, 23*, 992-1000. doi:http://dx.doi.org/10.1016/j.gloenvcha.2013.03.010

Maddison, D., & Bigano, A. (2003). The amenity value of the Italian climate. *Journal of Environmental Economics and Management, 45*, 319-332. doi:https://doi.org/10.1016/S0095-0696(02)00052-9

Maddison, D., & Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics, 70*, 2437-2445. doi:https://doi.org/10.1016/j.ecolecon.2011.07.027

Massey, D., Arango, J., Hugo, G., Kouaouci, A., Pellegrino, A., & Taylor, J. (1993). Theories of International Migration: A Review and Appraisal. *Population Development Review, 19*, 3. doi:https://doi.org/10.2307/2938462

Max-Neef, M. (1995). Economic growth and quality of life: a threshold hypothesis. *Ecological Economics, 15*, 115-118.

McAllistair, F. (2005). Wellbeing: Concepts and challenges. *Discussion Paper*. Retrieved from http://www.sd-research.org.uk/wellbeing/documents/SDRNwellbeingpaper-Final_000.pdf

Melbourne Institute. (2019). *The Household, Income and Labour Dynamics in Australia Survey:Selected Findings from Waves 1 to 17*. Retrieved from Melbourne:

Melbourne Institute. (2022). *Hilda Statistical Report*. Retrieved from Melbourne: https://melbourneinstitute.unimelb.edu.au/hilda/publications/hilda-statistical-reports

Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate Research, 27*(1), 19-31. Retrieved from https://www.int-res.com/abstracts/cr/v27/n1/p19-31/

Millenium Ecosystem Assessment. (2003). *Ecosystems and human wellbeing: a framework for assessment*. Retrieved from New York:

Mincer, J. (1978). Family Migration Decisions. *The Journal of Political Economy, 86*(5), 749-773.

Moro, M., Brereton, F., Ferreira, S., & Clinch, J. P. (2008). Ranking quality of life using subjective well-being data. *Ecological Economics, 65*, 448-460. doi:10.1016/j.ecolecon.2008.01.003

Mouratidis, K. (2018). Rethinking how built environments influence subjective well-being: a new conceptual framework. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 11*(1), 24-40. doi:https://doi.org/10.1080/17549175.2017.1310749

Mouratidis, K. (2019). Compact city, urban sprawl, and subjective well-being. *Cities, 92*, 261-272. doi:https://doi.org/10.1016/j.cities.2019.04.013

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica, 46*(1), 69-85. Retrieved from https://www.jstor.org/stable/1913646

Murray, T., Maddison, D., & Rehdanz, K. (2011). *Do geographical variations in climate influence life satisfaction?* Kiel Working Paper. Kiel Institute for the World Econoy.

Myers, D., & Diener, E. (1995). Who is happy? *Psychological Science, 6*(1), 10-19.

National Center for Environmental Information. (2018, 07/08/2020). What's the Difference between Weather and Climate? Retrieved from https://www.ncei.noaa.gov/news/weather-vs-climate

Neira, I., Bruna, F., Portella, M., & Garcia_Aracil, A. (2018). Individual Well-Being, Geographical Heterogeneity and Social Capital. *Journal of Happiness Studies, 19*, 1067-1090. doi:https://doi.org/10.1007/s10902-016-9840-z

Neuman, W. L. (2000). *Social Research Metdods: Quantitative and Qualitative Approaches*. Boston (MA): Allyn and Bacon.

Neumayer, E. (1999). The ISEW: not an index of sustainable economic welfare. *Social Indicators Research, 48*(1), 77-101.

Neumayer, E. (2000). On the methodology of ISEW, GPI and related measures: some constructive suggestions an some doubts on the 'threshold' hypothesis. *Ecological Economics, 30*, 347-361.

Newton, J. (2007). *Wellbeing and the natural environment: a brief review of the evidence*. Retrieved from

Ng, Y. K. (1997). A case for Happiness, Cardinalism and Interpersonal Comparability. *Economic Journal, 107*, 1848-1858.

Nisbet, E., & Zelenski, J. (2011). Underestimating Nearby Nature: Affective Forecasting Errors Obscure the Happy Path to Sustainability *Psychological Science, 22*(9), 1101-1106. doi:https://doi.org/10.1177/0956797611418527

Nitschke, M., Tucker, G., Hanse, A., Williams, S., Zhang, Y., & Bi, P. (2011). Impact of two recent extreme heat episodes on mortality and morbidity in Adelaide, South Australia: a case-series analysis. *Environmental Health, 10*(42). doi:https://doi.org/10.1186/1476-069X-10-42

NOAA. (2021). What is the difference between weather and climate? Retrieved from https://oceanservice.noaa.gov/facts/weather_climate.html

Nordhaus, W., & Tobin, J. (1973). Is Growth Obsolete? In M. Moss (Ed.), *The Measurement of Economic and Social Performance* (pp. 509-564). New York: National Bureau of Economic Research.

Nowok, B., van Ham, M., Findlay, A., & Gayle, V. (2013). Does migration make you happy? A longitudinal study of internal migration and subjective well-being. *Environment and planning A, 45*, 986-1002. doi:https://doi:10.1068/a45287

OECD. (2001). *The Well-being of Nations: The Role of Human and Social Capital*. Retrieved from Paris:

OECD. (2013). *OECD Guidelines on Measuring Subjective Wellbeing*. Retrieved from http://dx.doi.org/10.1787/9789264191655-en

OECD. (2020). *How's Life? 2020: Life Satisfaction*. Retrieved from https://www.oecdbetterlifeindex.org/topics/life-satisfaction/

Oishi, S., Kesebir, S., & Diener, C. (2011). Income inequality and happiness. *Psychological Science, 22*(9), 1095-1100. doi:https://doi:10.1177/0956797611417262

Oishi, S., Saeki, M., & Axt, J. (2015). Are People Living in Walkable Areas Healthier and More Satisfied with Life? *Applied Psychology: Health & Well-being, 7*(3), 365-383. doi:http://doi:10.1111/aphw.12058

Oishi, S., & Schimmack, U. (2010). Residential Mobility, Well-Being, and Mortality. *Journal of Personality and social psychology, 98*(6), 980-994. doi:http://doi:10.1037/a0019389

Oishi, S., & Tsang, S. (2022). The socio-ecological psychology of residential mobility. *Journal of Consumer Psychology, 32*, 519-536. doi:https://doi.org/10.1002/jcpy.1308

Oishi, S., & Westgate, E. (2021). A Psychologically Rich Life: Beyond Happiness and Meaning. *Psychological Review*. doi:http://dx.doi.org/10.1037/rev0000317

Okulicz-Kozaryn, A. (2011). Geography of European Life Satisfaction. *Social Indicators Research, 101*, 435-445. doi:http://doi.10.1007/sl1205-010-9671-y

Olvera Astivio, O., & Zumbo, B. (2019). Heteroskedasticity in Multiple Regression Analysis: What it is, How to Detect it and How to Solve it with Applications in R and SPSS. *Practical Assessment Research & Evaluation, 24*(1). Retrieved from http://pareonline.net/getvn.asp?v=24&n=1

Osberghaus, D., & Kuhling, J. (2016). Direct and indirect effects of weather experiences on life satisfaction – which role for climate change expectations? *Journal of Environmental Planning and Management, 59*(12), 2198-2230. doi:https://doi.org/10.1080/09640568.2016.1139490

Oswald, A., & Wu, S. (2011). Well-being across America. *The Review of Economics and Statistics, 93*(4), 1118-1134.

Palmore, E., & Luikart, C. (1972). Health and social factors related to life satisfaction. *Journal of Health and Social Behavior, 13*(1), 68-80.

Parker, P. M. (1995). *Climate effects on individual, social and economic behavior: A physioeconomic review of research across disciplines*. Westport, CT: Greenwood Press.

Parsons, K. (1993). *Human thermodynamic environments: The effects of hot, moderate and cold environments on human health, comfort and performance*. London: Taylor & Francis.

Parsons, K. (2020). *Human Thermal Comfort*. Retrieved from https://ebookcentral.proquest.com/lib/jcu/detail.action?docID=5982852.

Peace, A. (2015). Australia, Sociocultural Overviews: Australian Settler Society. *International Encyclopedia of the Social & Behavioral Sciences*, 239-244. doi:https://doi.org/10.1016/B978-0-08-097086-8.12022-7

Pek, J., Wong, O., & Wong, A. (2018). How to address non-normality: A Taxonomy of Approaches, Reviewed, and Illustrated. *Frontiers in Psychology, 9*. doi:https://doi:10.3389/fpsyg.2018.02104

Pittau, G., Zelli, R., & Gelman, A. (2010). Economic Disparities and Life Satisfaction in European Regions. *Social Indicators Research, 96*, 339-361. doi:DOI 10.1007/s11205-009-9481-2

Polgreen, L., & Simpson, N. (2011). Happiness and International Migration. *Journal of Happiness Studies, 12*, 819-840. doi:https://doi.10.1007/s10902-010-9229-3

Posner, S. M., & Costanza, R. (2011). A summary of ISEW and GPI studies at multiple scales and new estimates for Baltimore City, Baltimore County and the State of Maryland. *Ecological Economics, 70*, 1972-1980. doi:https://doi.org/10.1016/j.ecolecon.2011.05.004

Powdthavee, N. (2007). Are there geographical variations in the psychological cost of unemployment in South Africa? *Social Indicators Research, 80*, 629-652. doi:https://doi.10.1007/sl1205-006-0013-z

Queensland Government. (2017). *Pathways to a climate resilient Queensland-Queensland climate adaptation strategy 2017-2030*. Retrieved from https://www.des.qld.gov.au/climateaction/about/climate-adaptation

Ramlall, I. (2017). *Applied Structural Equation Modelling for Researchers and Practitioners:Using R and Stata for Behavioural Research*. Retrieved from https://ebookcentral.proquest.com/lib/jcu/reader.action?docID=4717018

Rappaport, J. (2007). Moving to nice climate. *Regional Science and Urban Economics, 37*, 375-398. doi:https://doi:10.1016/j.regsciurbeco.2006.11.004

Raudenbush, S., & Sampson, R. (1999). Ecometrics: Toward a Science of Assessing Ecological Settings, with Application to the Systematic Social Observation of Neighborhoods. *Sociological Methodology, 29*(1), 1-41. doi:https://doi.org/10.1111/0081-1750.00

Rehdanz, K., & Maddison, D. (2005). Climate and Happiness. *Ecological Economics, 52*, 111-125. doi:https://doi.org/10.1016/j.ecolecon.2004.06.015

Rehdanz, K., & Maddison, D. (2008). Local environmental quality and life-satisfaction in Germany. *Ecological Economics, 64*(4), 787-797. doi:http://doi:10.1016/j.ecolecon.2007.04.016

Rentfrow, P., Gosling, S., Jokela, M., Stillwell, D., Kosinski, D., & Potter, J. (2013). Divided We Stand: Three Psychological Regions of the United States and Their Political, Economic, Social, and Health Correlates. *Journal of Personality and social psychology*. doi:http://doi:10.1037/a0034434

Rentfrow, P., & Jokela, M. (2016). Geographical Psychology: The Spatial Organization of Psychological Phenomena. *Current Directions in Psychological science, 25*(6), 393-398. doi:https://DOI:10.1177/0963721416658446

Rentfrow, P., Jokela, M., & Lamb, M. (2015). Regional Personality Differences in Great Britain. *Plos one, 10*(3), e0122245. doi:https://DOI:10.1371/journal.pone.0122245

Rentfrow, P., Mellander, C., & Florida, R. (2009). Happy States of America: a state-level analysis of psychological, economic, and social well-being. *Journal of Research in Personality, 43*(6), 1073-1082. doi:https://psycnet.apa.org/doi/10.1016/j.jrp.2009.08.005

Rieger, E., Costanza, R., Kubiszewski, I., & Dugdale, P. (Eds.). (2023). *Toward an integrated science of wellbeing*. New York City: Oxford University Press.

Roysamb, E., Nes, R., Czajkowski, N., & Vassend, O. (2018). Genetics, personality and wellbeing: a twin study of traits, facets and life satisfaction. *Scientific Reports*. doi:https://doi.org/10.1038/s41598-018-29881-x

Roysamb, E., Tambs, K., Reichborn-Kjennrud, T., Neale, M., & Harris, J. (2003). Happiness and Health: Environmental and Genetic Contributions to the Relationship Between Subjective Well-Being, Perceived Health, and Somatic Illness. *Journal of Personality and social psychology, 85*(6), 1136-1146. doi:10.1037/0022-3514.85.6.1136

Royston, J. P. (1982). An Extension of Shapiro and Wilk's W Test for Normality to Large Samples. *Applied Statistics, 31*(2), 115-124. Retrieved from https://www.jstor.org/stable/2347973

Rubin, D. B. (2008). For Objective Causal Inference, Design Trumps Analysis. *The Annals of Applied Statistics, 2*(3), 808-840.

Sachs, J., Schmidt-Traub, G., Kroll, C., Lafortune, G., & Fuller, G. (2019). *Sustainable Develpment Report 2019*. Retrieved from New York:

San-Gil, J., Gonzalez de Rivera, J. L., & Gonzalez, J. (1991). Biometeorology of psychiatric disorders. In *The European Handbook of Psychiatry and Mental Health* (pp. 40-47).

Saucier, G. (1994). Mini_Markers: A Brief Version of Goldberg's Unipolar Big-Five Markers. *Journal of Personality Assessment, 53*(3), 506-516.

Schaller, M., & Murray, D. (2008). Pathogens, personality, and culture: disease prevalence predicts worldwide variability in sociosexuality, extraversion, and openness to experience. . *Journal of Personality and social psychology, 95*(1), 212-221. doi:http://doi:10.1037/0022-3514.95.1.212

Schimmack, U., & Oishi, S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. *Journal of Personality and social psychology, 89*, 395-406.

Schkade, D., & Kahneman, D. (1998). Does Living in California Make People Happy? A Focussing Illusiion in Judgments of Life Satisfaction. *Psychchological Science, 9*(5), 340-346. Retrieved from https://www.jstor.org/stable/40063318

Schneider, M. (1975). The quality of life in large American cities: Objective and subjective social indicators. *Social Indicators Research, 1*, 495-509. doi:https://doi.org/10.1007/BF00353066

Schwanen, T., & Wang, D. (2014). Well-being, context, and everyday activities in space and time. *Annals of the Association of American Geographers, 104*(4), 833-851. doi:https://doi:10.1080/00045608.2014.912549

Schynz, P. (2002). Wealth of nations, individual income and life satisfaction in 42 countries: a multi-level approach. *Social Indicators Research, 60*, 5-40.

Sekulova, F., & Van den Bergh, J. (2016). Floods and happiness: Empirical evidence from Bulgaria. *Ecological Economics, 126*, 51-57. doi:http://dx.doi.org/10.1016/j.ecolecon.2016.02.014

Shields, M., Price, S., & Wooden, M. (2009). Life satisfaction and the economic and social characteristics of neighbourhoods. *Journal of Population Economics, 22*, 421-443. doi:https://doi.org/10.1007/s00148-007-0146-7

Shucksmith, M., Cameron, S., Merridew, T., & Pichler, F. (2009). Urban–rural differences in quality of life across the European Union. *Regional Studies, 43*, 1275-1289. doi:https://doi.org/10.1080/00343400802378750

Silventoinen, K., Hammar, N., Hedlund, E., Koskenvuo, M., Ronnemaa, T., & Kaprio, J. (2007). Selective international migration by social position, health behaviour and personality. *European Journal of Public Health, 18*(2), 150-155. doi:http://doi:10.1093/eurpub/ckm052

Silvia, P., & Christensen, A. (2020). Looking up at the curious personality: individual differences in curiosity and openness to experience. *Current Opinion in Behavioral Sciences, 35*, 1-6. doi:https://doi.org/10.1016/j.cobeha.2020.05.013

Sinclair, M., O'Toole, J., Malawaraarachchi, M., & Leder, K. (2012). Comparison of response rates and cost-effectiveness for a community-based survey: postal, internet and telephone modes with generic or personalised recruitment approaches. *BMC: Medical Research Methodology, 12*.

Sjaastad, L. (1962). The costs and returns of human migration. *Journal of Political Economy, 70*(5), 80-93. Retrieved from https://www.jstor.org/stable/1829105

Snijders, T., & Berkhof, J. (Eds.). (2008). *Diagnostic Checks for Multilevel Models.* Berlin: Springer.

Snijders, T., & Bosker, R. (2011). *Multilevel Analysis: an Introduction to Basic and Advanced Multilevel Modelling (2nd edition)*: Sage Publications.

Speldewinde, P. C., Cook, A., Davies, P., & Weinstein, P. (2011). The hidden health burden of environmental degradation: disease comorbidity and dryland salinity. *EcoHealth, 8*(1), 82-92.

Stevenson, B., & Wolfers, J. (2008). *Economic Growth and Subjective Well-being: Reassessing the Easterlin Paradox*. Working paper Series, (WP14282). Cambridge (Mass).

Stewart, A. (2007). Linguistic dimensions of weather and climate perception. *International Journal of Biometeorology, 52*, 57-67. doi:https://doi10.1007/s00484-007-0101-z

Stiglitz, J., Sen, J., & Fitoussi, J. P. (2009). *Report of the Commission on the Measurement of Economic Performance and Social Progress*. Retrieved from https://ec.europa.eu/eurostat/documents/8131721/8131772/Stiglitz-Sen-Fitoussi-Commission-report.pdf

Stutzer, A., & Frey, B. (2008). Stress that doesn't pay: The commuting paradox. *Scandinavian Journal of Economics, 110*(2), 339-366. doi:https://doi:10.1111/j.1467-9442.2008.00542.x

Stutzer, A., & Frey, B. (2010). Recent Advances in the Economics of Individual Subjective Well-Being. *Social Research: An International Quaterly, 77*(2), 679-714.

Subramanian, S. V., Kawachi, I., & Kennedy, B. P. (2000). Does the state you live in make a difference? Multilevel analysis of self-rated health in the US. *Social Science and Medicine, 53*(1), 9-19.

Takano, T., Nakamura, K., & Watanabe, M. (2002). Urban residential environments and senior citizens, longevity in megacity areas: the importance of walkable green spaces. *Journal of Epidemiology and Community Health, 56*(12), 913-918.

Talberth, C. J., Cobb, C., & Slattery, N. (2007). *The Genuine Progress Indicator 2006, a Tool for Sustainable Development*. Oakland, CA: Redefining Progress.

Tellegen, A., Lykken, D., Bouchard, T., Wilcox, K., Segal, N., & Rich, S. (1988). Personality similarity in twins reared apart and together. *Journal of Personality and social psychology, 54*, 1031-1039.

Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning, 105*(3), 221-229. doi:https://doi.org/10.1016/j.landurbplan.2011.12.015

Tiebout, C. (1956). A pure economy of local expenditures. *Journal of Political Economy, 64*(5), 416-424.

Tsutsui, Y. (2013). Weather and individual happiness. *Weather, Climate, and Society, 5*(1), 70-82. doi:https://doi.org/10.1175/WCAS-D-11-00052.1

Twidale, C. R., Veevers, J., Lange, R. T., Richard, J. D., Roe, M., Powel, J. M., & Ride, W. D. L. (2023, 9/11/2023). Australia. Retrieved from https://www.britannica.com/place/Australia

Van de Vliert, E. (2013). Climato-economic habitats support patterns of human needs, stresses,and freedoms. *Behavioral and Brain Sciences, 36*, 465-521. doi:http://doi:10.1017/S0140525X12002828

Van de Vliert, E., Huang, X., & Parker, P. (2004). Do colder and hotter climate make richer societies more, but poorer societies less happy and altruistic? *Journal of Environmental Psychology, 24*, 17-30. doi:https://doi.org/10.1016/S0272-4944(03)00021-5

van den Bergh, J. (2009). The GDP paradox. *Journal of Economic Psychology, 30*, 117-135.

Van Kamp, I., Leidelmeijer, K., Marsman, G., & de Hollander, A. (2003). Urban environmental quality and human well-being:Towards a conceptual framework and demarcation of concepts; a literature study. *Landscape and Urban Planning, 65*, 5-18.

Van Praag, B. (1991). Ordinal and cardinal utily: an integration of the two dimensions of the welfare concept. *Journal of Econometrics, 50*, 69-89.

Van Praag, B., & Baarsma, B. (2005). Using happiness Surveys to value intangibles: the case of airport noise. *The Economic Journal, 115*, 224-246.

Van Praag, B., Frijters, P., & Ferrer-i-Carbonell, A. (2003). The anatomy of subjective wellbeing. *Journal of Economic Behavior and Organization, 51*(1), 29-49.

Vargas, N., & Magana, V. (2020). Warm Spells and Climate Risk to Human Health in the Mexico City Metropolitan Area. *Weather, Climate, and Society, 12*(3), 351-365. doi:https://doi.org/10.1175/WCAS-D-19-0096.1

Veenhoven, R. (1984). *Conditions of Happiness*. Dordrecht (Netherlands): Kluwer academic.

Veenhoven, R. (2000). Freedom and Happiness: a comparative study of 46 nations in the early 1990s. In E. Diener & E. Suh (Eds.), *Culture and Subjective wellbeing*. Cambridge (Mass): MIT Press.

Veenhoven, R. (2002). Why social policy needs subjective indicators. *Social Indicators Research, 58*, 33-45.

Veenhoven, R. (2008). *Comparability of Happiness across nations.* Paper presented at the International Meeting of the Psychometric Society, Tokyo, Japan.

Vemuri, A., & Costanza, R. (2006). The role of social, human, built and natural capital in explaining life satisfaction at the country level: Toward a Nation Wellbeing Index (NWI). *Ecological Economics, 58*, 119-133.

Vemuri, A., Grove, J. M., Wilson, M., & Burch, W. (2011). A Tale of Two Scales: Evaluating the Relationship Among Life Satisfaction, Social Capital, Income, and the Natural Environment at Individual and Neighborhood Levels in Metropolitan Baltimore. *Environment and Behavior, 43*(1), 3-25. doi:https://doi:10.1177/0013916509338551

Victor, P. (2022). *Herman Daly's Economics for a Full World: His Life and Ideas*. Oxford (UK), New York: Routledge.

Volker, S., & Kistemann, T. (2013). “I’m always entirely happy when I’m here!” Urban blue enhancing human health and well-being in Cologne and Düsseldorf, Germany. *Social Science and Medicine, 78*, 113-124. doi:http://dx.doi.org/10.1016/j.socscimed.2012.09.047

Watson, N. (2012). *Longitudinal and Cross-sectional Weighting Methodology for the HILDA Survey.* HILDA Project Technical Paper Series, (2/12). Melbourne.

Weckroth, M., Ala-Mantila, S., Ballas, D., Ziogas, T., & Ikonen, J. (2022). Urbanity, Neighbourhood Characteristics and Perceived Quality of Life (QoL): Analysis of Individual and Contextual Determinants for Perceived QoL in 3300 Postal Code Areas in Finland. *Social Indicators Research, 164*, 139-164. doi:https://doi.org/10.1007/s11205-021-02835-z

Welsch, H. (2002). Preferences over Prosperity and Pollution: Environmental Valuation based on Happiness Surveys. *Kyklos, 55*(4), 473-494.

Welsch, H. (2003). Freedom and rationality as predictors of cross-national happiness patterns: The role of income as ameditaing variable. *Journal of Happiness Studies, 4*, 295-321.

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological Economics, 56*, 801-813.

Welsch, H., & Ferreira, S. (2014). *Environment. Well-being and Experienced Preference*. Oldenburg Discussion Papers in Economics, (V347-14). Oldenburg Germany.

Wheaton, B., Waiti, J., Cosgriff, M., & Burrows, L. (2020). Coastal blue space and wellbeing research: looking beyond western tides. *Leisure studies, 39*(1), 83-95. doi:http://doi:10.1080/02614367.2019.1640774

Wheeler, D., & Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients in geographically weighted regressions. *Journal of Geographical Systems, 7*, 161-187. doi:https://doi.org/10.1007/s10109-005-0155-6

White, H. (1980). A Heteroskedasticity Resistant Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica, 48*(4), 817-838. doi:https://doi:10.2307/1912934

White, M., Alcock, I., Wheeler, B., & Depledge, M. (2013). Would You Be Happier Living in a Greener Urban Area? A Fixed-Effects Analysis of Panel Data. *Psychological Science, 24*(6), 920-928. doi:https://doi:10.1177/0956797612464659

White, M., Pahl, S., Wheeler, B., Depledge, M., & Fleming, L. (2017). Natural environments and subjective wellbeing: Different types of exposure are associated with different aspects of wellbeing. *Health and Place, 45*, 77-84. doi:http://dx.doi.org/10.1016/j.healthplace.2017.03.008

Wilkinson, R., & Pickett, K. E. (2009). *The spirit level. Why more equal societies almost always do better.* UK: Bloomsbury Publishing.

Williams, J., Hook, R. A., & Hamblin, A. (2002). *Agro-ecological regions of Australia: methodologies for their derivation and key issues in resource management*. Canberra: CSIRO Land and Water.

Wilson, W. (1967). Correlates of Avowed happiness. *Psychological Bulletin, 67*(4).

Wooldridge, J. (2010). *Introductory Econometrics: A Modern Approach.* (5th ed.). Australia: South Western.

World Bank. (2023a). Australia Unemployment Rate 1991-2023. In: MacroTrends.

World Bank. (2023b). Unemployment (% of total workforce)(modeled ILO estimate)-United Kingdom. Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?locations=GB

Yang, Z., Yang, B., Liu, P., Zhang, Y., & Yuan, X. C. (2021). Impact of temperature on physical and mental health: evidence from China. *Weather, Climate, and Society, 13*(4), 709-727. doi:https://doi.org/10.1175/WCAS-D-21-0038.1

Yee, T. N., Nai, P. T., & Eu, C. T. (2015). Determinants of Life Satisfaction in Asia. *Social Indicators Research, 124*, 141-156. doi:http://doi.10.1007/s11205-014-0772-x

Yuan, H. (2016). Structural Social Capital, Household Income and Life Satisfaction: The Evidence from Beijing, Shanghai and Guangdong-Province, China. *Journal of Happiness Studies, 17*(2), 569-586. doi:https://doi.10.1007/s10902-015-9622-z

Zander, K., & Garnett, S. (2020). The importance of climate to emigration intentions from a tropical city in Australia. *Sustainable Cities, 63*(102465). doi:https://doi.org/10.1016/j.scs.2020.102465

Zander, K., Moss, S., & Garnett, S. (2019). Climate Change–Related Heat Stress and Subjective Well-Being in Australia. *Weather, Climate, and Society, 11*(3), 505-520. doi:https://doi.org/10.1175/WCAS-D-18-0074.1

Zhou, J., & Xie, Y. (2016). Does Economic Development Affect Life Satisfaction? A spatial-Temporal- Contextual Analysis in China. *Journal of Happiness Studies*(17), 643-658.

Ziogas, T., Ballas, D., Koster, S., & Edzes, A. (2023). Happiness, Space and Place: Community Area Clustering and Spillovers of Life Satisfaction in Canada. *Applied Research in Quality of Life*. doi:https://doi.org/10.1007/s11482-023-10203-x

Appendix: Electronic survey questionnaire

Climate and Life Satisfaction Survey

Intro **Would you like to help us find out how the climate and the natural environment are affecting your wellbeing?**

PARTICIPANT INFORMATION STATEMENT PROJECT TITLE: Influence of climate factors on life satisfaction in Australia
(Human Research Ethics Committee approval # H8397) **Would you like to help us find out how the climate and the natural environment are affecting your wellbeing?** You are invited to participate in an **online survey** that is part of our project investigating the relationship between local climate, natural environment, and individual life satisfaction. This study is being conducted by **Phil Lignier** and will contribute to a PhD project in Economics at **James Cook University**. The project has received the financial support of the College of Business, Law and Governance at James Cook University. If you are happy to help us and take part in this survey, you will only need to complete a once-off online questionnaire:
-This will only take approximately **10 minutes**.
-Your participation is **completely voluntary.**
-You may decide to **withdraw at any time** without explanation or prejudice.
-By completing this questionnaire, you are eligible to participate in a **prize draw** where you can win a **$100 gift voucher.**

We do not anticipate any risks to you resulting from your participation in this research. However, please note that as this is an anonymous survey, if you choose to withdraw from the survey

before completing the questionnaire, data already collected cannot be deleted.

By completing this questionnaire, you are eligible to participate in a **prize draw** where you can win a **$100 gift voucher.** Your responses will remain strictly **anonymous**:

-The details we used to contact you (email or postal address) are not traceable from your survey responses.

-Your survey responses will be saved electronically and stored in a confidential database.

-Your computer IP address, which is automatically logged when you submit your survey online, will be deleted immediately upon receipt.

-To prevent unauthorised access, all survey responses will be stored electronically on the **secure, password-protected,** James Cook University cloud storage system.

At the end of the survey, you will be asked whether you are willing to provide your contact email if you wish to participate in the prize draw. Please note that this is entirely **voluntary**. If you accept, your contact details will be collected and stored apart from the survey data, so that there is no way to link your email address to your survey responses, thus ensuring the anonymity of those responses. The conduct of this research involves the collection of information you may regard as private. This information will not be disclosed to any third party without your consent, except to meet government, legal or other regulatory authority requirements. A de-identified copy of this data may be used for other research purposes. However, your anonymity will at all times be safeguarded. For further information, you may consult James Cook University Right-to-Information and Privacy policy at https://www.jcu.edu.au/right-to-information-and-privacy. If you have any questions about the study, please contact **Phil Lignier (Principal investigator)** or **Dr Diane Jarvis (Primary Advisor and co-investigator)**.

Principal Investigator:
Phil Lignier
College of Business Law & Governance
James Cook University
Phone:
Email:

Primary Advisor / co-investigator: Dr Diane Jarvis
College of Business, Law & Governance
James Cook University
Phone:
Email:

If you have any concerns regarding the ethical conduct of the study, please contact: Human Ethics, Research Office
James Cook University, Townsville, Qld, 4811
Phone:

Consent I consent to take part in this survey

O Yes (1)

O No (2)

NC Thank you for your time!

Q1 In which state or territory do you live?

- O Queensland
- O Tasmania
- O New South Wales
- O Australian Capital Territory
- O Victoria
- O South Australia
- O Western Australia
- O Northern Territory

Q2 In what town/suburb do you live?

_____

Q3 What is your postcode?

- O Click to enter a four-digit postcode

_____

Q4 Is the place where you live most of the time: *(Select one*)

- O In a town/ suburb or village?
- O on a farm?
- O on a rural property not used for farming?

Q5 How many years have you lived in your current community? *(Select one)*

- O Less than a year
- O 1 to 2 years
- O 3 to 4 years
- O 5 to 9 years
- O 10 to 14 years
- O 15 to 19 years
- O 20 years or more
- O All my life

Q6 How likely are you to shift to **another area** within the next 12 months? *(Select one)*

- O Extremely unlikely
- O Somewhat unlikely
- O Neither likely nor unlikely
- O Somewhat likely
- O Extremely likely

Q7
All things considered, how satisfied are you with your life overall?
(Choose your score from 0 to 10 by moving the cursor on the sliding rule: 0 = totally dissatisfied, 10= totally satisfied)

0 (0) 1 (1) 2 (2) 3 (3) 4 (4) 5 (5) 6 (6) 7 (7) 8 (8) 9 (9) 10 (10)

Q8 **Compared to 2019**, how satisfied are you with life overall now? *(Select one)*

- O I am much more satisfied with my life now than I was in 2019.
- O I am somewhat more satisfied with my life now than I was in 2019.
- O About the same as I was in 2019.
- O I am somewhat less satisfied with my life now than I was in 2019.
- O I am much less satisfied with my life now than I was in 2019.

Q9 What is your gender?

- O Female
- O Male
- O Prefer not to say.

Q10 What is your age?

- O 24 or younger
- O 25 - 39
- O 40 - 54
- O 55 - 69
- O 70 - 84
- O 85 or older
- O Prefer not to say.

Q11 Are you: (*Select one*)

- O Married or in a relationship?
- O Widowed?
- O Divorced or separated?
- O Never married?
- O Separated?

Q12 Do you identify as Aboriginal or Torres Strait Islander? *(Select one)*

- O Yes, Aboriginal
- O Yes, Torres Strait Islander
- O Yes, both Aboriginal and Torres Strait Islander
- O No

Q13 What is the **highest** level of education you have attained? *(Select one)*

- O Year 10 or below
- O Year 11 or 12
- O TAFE Certificate or equivalent
- O TAFE Diploma or equivalent
- O Undergraduate university degree
- O Postgraduate university degree (e.g., Masters, Doctorate, Postgraduate Certificate or Diploma)

Q14 What **best** describes your current employment situation? *(Select one)*

- O I am in full-time employment
- O I am in part-time employment
- O I am self-employed (own a business)
- O I am a full-time student
- O I am currently unemployed
- O I am retired

Q15 In the 2019/20 Financial year, how much was your household income **before taxes**? (*Select one)*

- O $0- $10,399
- O $10,400- $25,599
- O $25,600- $41,599
- O $41,600- $57,199
- O $57,800-$72,799
- O $72,800-$88,399
- O $88,400-$103,999
- O $104,000 -$135,199
- O $135,200- $181,999
- O $182,000-$259,999
- O $260,000 or more
- O Prefer not to say

Q16 Given your current needs and financial responsibility, would you say that you and your family are: (*Select one)*

- O Prosperous
- O Very comfortable
- O Reasonably comfortable
- O Struggling
- O Poor

Q17 Thinking about **the past 12 months**, how often did you engage in the following outdoor activities? (*Click on the appropriate circle for each activity)*

	Not at all (1)	Rarely (2)	A few times a year (3)	Once or twice a month (4)	About once a week (5)	Every day or most days (6)	Not Applicable (7)
Outdoor activities to do with farming (incl. hobby farming) (1)	O	O	O	O	O	O	O
Outdoor activities to do with a job, trade or occupation other than farming (2)	O	O	O	O	O	O	O
Gardening or beekeeping (3)	O	O	O	O	O	O	O
Outdoor sporting activities (incl. sailing or flying) (4)	O	O	O	O	O	O	O
Walking as part of my domestic activities (e.g., shopping, school, etc.) (5)	O	O	O	O	O	O	O
Walking to/ from work (6)	O	O	O	O	O	O	O
Cycling/ motorcycling as part of my domestic activities (7)	O	O	O	O	O	O	O

Cycling/ motorcycling to/ from work (8)	O	O	O	O	O	O	O
Recreational walking (9)	O	O	O	O	O	O	O
Recreational cycling (10)	O	O	O	O	O	O	O
Recreational motorcycling (11)	O	O	O	O	O	O	O
Fishing or hunting (12)	O	O	O	O	O	O	O

Q18A In general, would you say that your health (including your mental health) is: *(Select one)*

O Excellent

O Very Good

O Good

O Fair

O Poor

Q18B **Compared to 2019**, how would you rate your health now? *(Select one)*

- O Much better now than in 2019
- O Somewhat better now than in 2019
- O About the same as in 2019
- O Somewhat worse now than in 2019
- O Much worse now than in 2019

INFO *In this section, we are asking you questions about the **climate** in your area. Climate is not the same as weather. While weather is what you get on a given day, climate depicts what the weather is like in a particular area over a long period of time.*

Q19 What **best** describes how you feel about the climate in the area where you live? (*Select one)*

O The climate where I live is fantastic; I wouldn't live anywhere else with a different climate. (1)6

O I like the climate where I live most of the time.

O I put up with the climate where I live even though I don't always like it.

O I don't like the climate where I live; I wish I could move somewhere with a different climate. (4)

O The climate where I live is awful; I would like to move somewhere with a different climate. (5)

O The climate doesn't really matter to me; the area where I live is as good as anywhere else in that respect. (6)

Q20 Please indicate your **degree of agreement** with the following statements about the climate in the area where you live. (*Select the box that indicates your level of agreement)*

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
It is too cold in Winter where I live. (1)	O	O	O	O	O
It is too hot in Summer where I live (2)	O	O	O	O	O
It rains too much/too often where I live. (3)	O	O	O	O	O
It is often too windy where I live. (4)	O	O	O	O	O
The area where I live is prone to flooding. (8)	O	O	O	O	O
The area where I live is prone to bushfires. (9)	O	O	O	O	O
The area where I live is prone to cyclones. (10)	O	O	O	O	O
The area where I live is prone to long and severe droughts. (11)	O	O	O	O	O
It is often sunny where I live (5)	O	O	O	O	O
The climate where I live is good for my physical health. (6)	O	O	O	O	O
The climate where I live is good for my mental health and wellbeing. (7)	O	O	O	O	O

Q21

Natural environment may refer to green space (forests, parks, gardens, etc) or natural scenery (water, mountains, sky, etc) in your immediate surroundings or in the broader area where you live.

Please select statements about the natural environment where you live that apply to you.
(*You may select more than one statement)*

- ☐ The natural environment where I live has restorative healing effects on my physical health.
- ☐ The natural environment where I live encourages me to exercise.
- ☐ The natural environment where I live relieves my stress.
- ☐ The natural environment where I live relieves me from depression and anxiety.
- ☐ The natural environment where I live gives me a feeling of safety and security.
- ☐ The natural environment where I live gives me a sense of place (I feel I belong here)
- ☐ The natural environment where I live benefits my spiritual wellbeing.
- ☐ The natural environment doesn't really matter to me. The area where I live is as good as anywhere else in that respect.

Q22 Please indicate your degree of agreement with the following statements about the natural environment in the area where you live. (*Select the box that indicates your level of agreement)*

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Air pollution is high in the area where I live. (3)	O	O	O	O	O
Noise levels are high in the area where I live. (4)	O	O	O	O	O
Water pollution is high in the area where I live. (5)	O	O	O	O	O
Litter pollution is high in the area where I live. (6)	O	O	O	O	O
I live near an unpleasant /unhealthy facility (e.g., landfill, sewage treatment plant, HV power line …). (7)	O	O	O	O	O
I live within walking distance from green space. (10)	O	O	O	O	O
There are many safe walking tracks in green space near where I live. (11)	O	O	O	O	O
There are many safe biking tracks in green space near where I live. (12)	O	O	O	O	O
I live within a short driving distance from a conservation area (national park…) or unspoilt beaches. (8)	O	O	O	O	O
There is a lot of beautiful scenery in the area where I live. (1)	O	O	O	O	O

Q23 What best describes your household? *(Select one)*

- O Sole person household
- O Couple only household
- O Single parent with children household
- O Couple parent with children household
- O Share or group household
- O Other (6)

Q23B Please specify.

_____

Q24 Are you renting, paying off a mortgage or do you/ your family own your home outright? (*Select one)*

- O I am "couch-surfing" staying temporarily with others.
- O I am renting.
- O I (and my partner) own my/ our home with a mortgage.
- O I (and my partner) own my/ our home outright.
- O I live in a home without paying rent.

Q25 Please describe the home you are currently living in. (*Select one)*

- O Freestanding house
- O Townhouse
- O Unit/ apartment
- O Retirement village
- O Aged care residence
- O Other: e.g., caravan, houseboat, tent, temporary building

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Q25B Please specify.

_____

Q26 Please select statements that apply to your home at the moment. *(You may select more than one statement)*

- ☐ Overall, my (our) home meets my (our) needs well.
- ☐ My (our) home is well maintained.
- ☐ My (our) home warms up very fast in hot weather.
- ☐ My (our) home gets cold when the temperature outside drops.
- ☐ My (our) home has adequate cooling installed.
- ☐ My (our) home has adequate heating installed.

Q27 Would you like to participate in the **prize draw** and win a $100 Gift voucher? *(If you click "Yes" you will be redirected to separate survey site where you will be invited to leave your email address)*

- O Yes
- O No