Measuring the relationship between the natural environment and subjective well-being

Sarah Jane Knight

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University of York

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Abstract

There is growing consensus that exposure to the natural environment is beneficial for human well-being. However, some studies examining this relationship do not find significant associations. Findings can often be inconclusive, and comparative studies are difficult given the breadth of well-being measures, natural environment metrics, analytical techniques and spatial units applied. I explored how type and quality of the natural environment are associated with subjective well-being in adults in England. I identified air pollution, specifically nitrogen dioxide (NO_2), land use and habitat type, site designation, and biodiversity as measures of characteristics of the natural environment. I used different methods to capture exposure, using neighbourhood proportion, network analysis and distance-decay. I used longitudinal individual-level data from the British Household Panel Survey and the UK Household Panel Study, and up to three well-being measures to examine the multi-dimensional nature of well-being. My results suggest that NO_2 has a negative association with subjective well-being in England. I found proximity to bluespaces, sites that are designated as important for nature conservation, and having access to private open space are all important for subjective well-being in London. I found that habitat diversity is not important for well-being, but that certain habitat types are. Several land uses and habitat types have positive associations with well-being in London (e.g. golf courses, allotments, playing fields, equestrian centres, and herb-rich grassland), and others have negative associations (e.g. woodland). I found some evidence of a relationship between well-being and biodiversity, as measured by butterfly and bird species richness and Normalised Difference Vegetation Index (NDVI). Overall, these relationships differ between population sample, well-being measure and exposure methods. The effect size of exposure to the natural environment is small (although often comparable to other key determinants of well-being). However, if this effect is experienced widely across communities and society, the cumulative effect could be significant.

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Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

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Chapter 1: General Introduction

1.1 Introduction

Urbanisation is described as one of the world's current major threats to health (World Health Organisation 2016). Despite urban populations benefitting from, generally, better economic prosperity, better sanitation, nutrition and health care (Dye 2008), city dwellers are more at risk from chronic, non-communicable and mental health conditions (Cox *et al.* 2017; Dye 2008; Lederbogen *et al.* 2011; Peen *et al.* 2010). Growing incidence of conditions such as depression have been attributed to the modern urban environment (Hidaka 2012), and urban populations are more likely to experience mood and anxiety disorders than their rural counterparts (Peen *et al.* 2010).

Urban areas are also increasingly more crowded and polluted than rural areas (Dye 2008), and this means there is less space for nature (Cox *et al.* 2018). With two-thirds of the global human population estimated to be living in urban environments by 2050 (World Health Organisation 2016), cities are likely to densify, resulting in the decrease in quantity and quality of urban green- and bluespaces, and the increase in environmental risks, such as poorer air quality. In fact, this is already occurring in cities across the world (European Environment Agency 2018; Haaland & van den Bosch 2015). Across Europe for example, city size was found to be positively related to total green space area, but urban densification led to cities with higher population densities having lower green space per capita (Fuller & Gaston 2009). Loss of urban greenspace due to infilling and redevelopment is reported in Europe and Australia (Haaland & van den Bosch 2015). In England, urban greenspace reduced by 8% between 2001-2018, from 63% to 55% (Committee on Climate Change 2019). Globally, urban areas are predicted to triple in size by 2030 (from 2010 extents) to accommodate an increasingly urban population (Seto *et al.* 2012). Modern urbanisation is more rapid and non-linear than that seen historically, therefore the preservation of urban natural environments becomes more important than ever before (Ramalho & Hobbs 2012).

Proximity and exposure to the natural environment has been found to be beneficial for human health and well-being (Barton & Pretty 2010; Maas *et al.* 2006; Mitchell & Popham 2008; Twohig-Bennett & Jones 2018). This is particularly important in urban environments, where environmental 'bads' such as air pollution and noise have been attributed to poor health (Dadvand *et al.* 2015; Nowak *et al.* 2014; Tzivian *et al.* 2015). Additionally, some evidence suggests beneficial associations in rural areas (Alcock *et al.* 2015), and therefore should be considered in studies too.

The recognition of the salutogenic benefits of the natural environment is reflected in the recent increase of broad global agreements to address the quality and provision of urban green and blue spaces in relation to human health. For example, the UN Sustainable Development Goals aim for universal access to good quality and accessible green spaces in cities by 2030 (United Nations 2017). The World Health Organisation's European Healthy Cities Network sets out a vision for physical environments that enable and drive health and well-being for all (World Health Organisation 2018). At a national level, one of the six key policy areas in the UK government's 25 Year Environment Plan is to connect people to nature to improve health and well-being (HM Government 2018).

However, there is very little consistent information regarding how to implement these broad statements about nature provision, quality and exposure, and it is often left open to interpretation (Douglas *et al.* 2017; Hunter *et al.* 2019). Essentially, the link between research, guidance and implementation is missing (Crawford 2010). Additionally, there are key gaps in our understanding about how facets of the natural environment relate to well-being. In a recent review, Bratman *et al.* (2019) summarise them as follows: natural features (size, type, qualities), exposure (proximity, time spent), experience (interaction, dose), and effects (mental health, psychological well-being). In this introduction, I will explore how well-being and the natural environment are defined and measured in the literature, describe our current understanding of how well-being is related to the natural environment, and discuss the various approaches to capturing and estimating exposure. I will highlight the current gaps in our understanding and finish by identifying how this thesis contributes to this research area.

1.2 What is well-being?

Well-being has been described as a "multi-dimensional, dynamic, person-specific and culture-specific" phenomena, with both objective or subjective components (King *et al.* 2014). The relationship between humans and the natural environment is explored in many different disciplines, for example economics, geography, biology, medicine, health, psychology, anthropology and history (Keniger *et al.* 2013). Discipline, context, and culture all play a part in how the natural environment and well-being are defined (Taylor & Hochuli 2017). Traditionally, objective measures have been used as proxies for well-being. These include income, gross domestic product (GDP) or presence of a health condition (Brereton *et al.* 2008), or the more recent inclusion of physiological metrics, such as cognitive functioning, brain response or stress-response measures (Laumann *et al.* 2003; Tilley *et al.* 2017). Subjective well-being relates to one's own perception and experience of their life. It has been defined as 'a good mental state, including all the various evaluations, positive and negative, that people make of their lives and the affective reactions of people to their experiences' (OECD 2013). Or more concisely it is 'a person's cognitive and affective evaluations of his or her life' (Diener *et al.* 2002). Both objective and subjective well-being measures are commonly used in the nature-well-being literature (Kondo *et al.* 2018). For example, objectively measured diurnal salivary cortisol changes and self-reported levels of vitality or stress (Roe *et al.* 2013; Tyrväinen *et al.* 2014).

There are said to be three aspects of subjective well-being (Brown 2015). The first is eudaemonic well-being, which refers to a broad feeling of contentment, meaningfulness and self-realisation (Helliwell 2006). The second is hedonic well-being, the affective and experiential component of well-being, describing short term pleasure or momentary happiness, with the absence of pain (Ryan & Deci 2001). Affect can be both positive and negative, and they are not necessarily opposite ends of the same spectrum (McMahan & Estes 2015). The third is life satisfaction, the evaluative or cognitive component of well-being, relating to the evaluation of one's own life. These are now recognised to be different phenomena, that it is possible to have one without the other, and that individuals differ in their decisions, preferences, and drivers for each (Adler *et al.* 2017; Diener *et al.* 1999; Feldman 2019).

1.2.1 What impacts subjective well-being?

Economic and psychology literature have long explored the determinants of subjective well-being (Di Tella & Macculloch 2006). At the individual level, there are well understood relationships between subjective well-being and, for example, genetics, age, marital status, income, employment status and health (Dolan *et al.* 2008). Therefore, in order to isolate the effect of the natural environment on well-being it is important to account for these variables in the study design.

Health and well-being are two fundamentally linked phenomena. As a key determinant of subjective well-being, health, therefore, is closely related to, and often used interchangeably with, the term 'well-being'. Indeed, research shows that individuals often rank their own health of higher importance than their subjective well-being, believing that good health is a precursor to well-being (Adler *et al.* 2017). If feeling good is an element of well-being, then health almost certainly underpins well-being. For instance, the UK's Office for National Statistics places health as a key determinant of well-being. The Millennium Ecosystem Assessment also places health as a determinant of well-being, as well as other factors such as social cohesion and a sense of value and achievement (Millennium Ecosystem Assessment 2005). This is also supported in much of the literature that examines the determinants of well-being (Adler *et al.* 2017; Dolan *et al.* 2008).

Health is a basic element of human life. The World Health Organisation (WHO) defines health as 'a state of complete physical, mental and social well-being and not merely the absence of disease'. However recent criticisms of this definition suggest it leads to the medicalisation of health (Bircher & Kuruvilla 2014). Criticisms recognise that this definition is almost unachievable and excludes those with disabilities, non-communicable and chronic health conditions, who may report to feel healthy, despite their conditions (Adler *et al.* 2017). Recent public health work recognises the evaluative, and therefore subjective nature of health, and studies show that health is consistently associated with subjective well-being, but the relationship is differentiated by the separate domains of subjective well-being (Miret *et al.* 2017). Health has been described as 'an adaptive state' (Sturmberg 2014), that is constantly responding and changing according to the biological, social, emotional and cognitive states of the individual (Sturmberg 2014).

Health therefore, like well-being, can be described as being personal, evaluative and changing through time. There are generally two models of health: the biomedical and the social. The biomedical model sees health as objective and measurable, the social as socially constructed and political. Huber et al., (2011) describe three types of health: physical (allostasis), mental (sense of coherence) and social. The latter refers to an individual's ability to cope, manage and adapt to conditions. They suggest that an improvement in a practical sense for health care professionals would be to not only assess functional status, but to also measure quality of life and sense of well-being.

There are several groups of health measurements that are currently used to assess health in healthcare settings (Lovell 2018). For example, as well as functional status measures such as physical fitness, presence of disease or illness, and psychological and physiological functioning, they also include subjective measures such as self-reported health status, quality of life measures and qualitative approaches to the lived experience of health or illness. This inclusion of subjective as well as objective health measures is important as it is entirely plausible that an individual in poor objectively measured health could report high levels of well-being (Adler *et al.* 2017).

1.2.2 Measuring subjective well-being

Across well-being and nature literature there are many measures of subjective well-being. For example, the most common measures include life satisfaction (White *et al.* 2013b, 2013a, 2017, 2019), mental distress (as measured by the General Health Questionnaire (GHQ)) (Alcock *et al.* 2015; Astell-Burt *et al.* 2014c; de Vries *et al.* 2003; Pasanen *et al.* 2019; White *et al.* 2013b, 2013a), and self-reported general health (de Vries *et al.* 2003; Garrett *et al.* 2019b; Mears *et al.* 2019a; Pasanen *et al.* 2019; White *et al.* 2013a, 2019). Other less common measures include perceived happiness (Krekel & MacKerron 2020; White *et al.* 2017), anxiety and feeling your activities are meaningful/worthwhile (White *et al.* 2017), the World Health Organisation WHO 5-item Wellbeing Index (WHO-5) (Garrett *et al.* 2019b), the Profile of Mood States (Pretty *et al.* 2005; Takayama *et al.* 2014), the Restorative Outcome Scale (Takayama *et al.* 2014), the Subjective Vitality Scale (Takayama *et al.* 2014), and the Positive and Negative Affect Scale (Takayama *et al.* 2014).

A life satisfaction question, the GHQ, and self-reported general health are commonly used tools in surveys to capture subjective well-being. Life satisfaction is the most commonly used internationally (e.g. Helliwell et al., 2020). It is usually based on the respondents' answer to the following question: 'How dissatisfied or satisfied are you with life overall?' The GHQ is widely used in literature as a measure of mental health, or more accurately it is a measure of mental distress (Gascon *et al.* 2015). Respondents are asked to self-assess against positive and negative statements (e.g. I am capable of making decisions and I think of myself as worthless), based on their own evaluation of how the "past few weeks" compare with "usual". Self-reported general health is also used widely in the human-nature literature and has been tested as a valid and reliable measure of general health (Brown 2015). There is a large body of research that examines the reliability and validity of measures of subjective well-being (Diener *et al.* 2013; Frey *et al.* 2010). Despite several potential limitations, subjective measures of well-being have been shown to have a high scientific standard in terms of internal consistency, reliability and validity (Frey *et al.* 2010; OECD 2013).

In England and the UK, common datasets used to study well-being and the natural environment include the British Household Panel Survey (BHPS) (Alcock *et al.* 2015; Astell-Burt *et al.* 2014c; White *et al.* 2013a, 2013b) and the Monitoring Engagement with the Natural Environment (MENE) (de Bell *et al.* 2017, 2020b; White *et al.* 2019; Wyles *et al.* 2019). Less frequently used are the UK Household Longitudinal Survey (Houlden *et al.* 2017), the Health Survey for England (Pasanen *et al.* 2019) and that collected under the Mappiness project (MacKerron & Mourato 2013).

Efforts to understand what drives well-being and how to best measure well-being are crucial to implementing effective well-being policies. In 2012, for instance, the UK's Office for National Statistics published its first index of subjective well-being, as part of the government's Measuring National Well-Being project. This index provided evidence for the national state of quality of life and is used across UK government to drive decision-making and policy analysis. The UK has also officially backed the United Nation's Sustainable Development Goals (SDGs) which, among other things, strive for good health and well-being (SDG 3; United Nations, 2015). Globally, countries are introducing measures that signal an economic shift towards including human and ecological well-being in measures of progress, such as the Wellbeing Economy Governments (WEGo: Scotland, Iceland, New Zealand, and Wales). This initiative recognises that current methods for assessing prosperity and progress, such as Gross Domestic Product (GDP) are insufficiently capturing the holistic nature of welfare, and leading to environmental degradation (Costanza 2014).

1.2.3 Environmental valuation and well-being

Well-being measures have recently been used in environmental valuation, using a series of techniques to ascribe value to environmental goods (Atkinson *et al.* 2018). Unfortunately environmental amenities often do not have prices and will therefore be typically underprovided by the market (Pendleton *et al.* 2007). This undervaluation of non-market environmental goods has important implications when policies and management practices are based upon inaccurate and incomplete figures (Schleicher *et al.* 2018). In order to provide a clear rationale for environmental management and regulation, it is important to calculate how much value people attribute to environmental features (Srinivasan & Stewart 2004; Welsch & Kühling 2009).

Typically economists have relied on stated and revealed preference methods to estimate the utility gains/losses associated with changes in the provision of non-market environmental goods and services (Egan *et al.* 2015; Kuminoff *et al.* 2010). However, these techniques and their underlying assumptions have been criticised for their uses in environmental valuation. For example, stated preference methods are susceptible to hypothetical bias and framing problems (Lusk & Norwood 2009; Murphy *et al.* 2005), and revealed preference methods rarely estimate for long-term discount rates and wrongly assume a set of market relationships exist for valuing environmental goods (Bartolini & Sarracino 2018; Brown 2015). These methods have also been criticised more broadly for their uses in environmental valuation (Spangenberg & Settele 2010). For example, it is suggested that they place focus on the utilitarian viewpoint that the environment is there for human gain (instrumental and non-use values), and that valuation often fails to capture the intrinsic values held about nature by people (Pearson 2016). Moreover, these traditional economic valuation methods are based upon different ontological and axiological assumptions to how individuals may experience, value and gain benefits from the natural environment (Cooper *et al.* 2016).

In response to these criticisms, the use of subjective well-being data has been increasingly used as a mechanism for communicating the well-being effects stemming from exposure to environmental (dis)amenities (Ferreira & Moro 2010). This approach is called the experienced preference method (Fernandez *et al.* 2019), and is often further used to elicit monetary value, known as the life satisfaction approach (Frey *et al.* 2010).

The life satisfaction approach has been used, for example, to derive a value associated with ecosystem diversity (Ambrey & Fleming 2014), airport noise (van Praag & Baarsma 2005), flood disasters (Luechinger & Raschky 2009) and flood avoidance (Fernandez *et al.* 2019), climate (Maddison & Rehdanz 2011), weather (Barrington-Leigh & Behzadnejad 2017b), scenic amenity (Ambrey & Fleming 2011), greenspace (Krekel *et al.* 2016; Tsurumi & Managi 2015) and air quality (Ambrey *et al.* 2014; Barrington-Leigh & Behzadnejad 2017a; Ferreira *et al.* 2013; Levinson 2012; Luechinger 2009; Mackerron & Mourato 2008; Orru *et al.* 2016; Zhang *et al.* 2017a). While not without its own limitations, this approach avoids some of the difficulties inherent with stated and revealed preferences. For example, it is less likely to suffer from hypothetical bias and framing problems, it is less cognitively demanding for respondents, and it neither presumes rational agents nor does it need to rely on assumed equilibrium in private market transactions to estimate the value of public goods (Ferreira & Moro 2010; Neuteleers & Engelen 2015).

1.3 What is the natural environment?

The physical environment as a determinant of health and well-being has recently seen a lot of attention and research, and there is a lot of evidence to suggest that facets of the natural environment play a significant role in predicting human health and well-being (Hartig *et al.* 2014; Maas *et al.* 2009b). Indeed, this is the focus of the recently published World Happiness Report 2020 (Helliwell *et al.* 2020). Better understanding how the natural environment impacts individual well-being is a key area of research interest.

However, defining the natural environment is in itself complicated. There are several terms commonly used across the literature to refer to it: for example nature, natural capital, and green- and bluespaces. Nature is the common term in social science literature (e.g. Berman *et al.* 2008; de Bell *et al.* 2017; Ray & Jakubec 2014). Nature is a broad term that refers to anything that is perceived as natural; it extends beyond specific typologies of places and spaces. Nature is described as the physical features and processes of nonhuman origin, distinguishing between animals, plants, air, weather and landscapes (Hartig *et al.* 2014; Pascual *et al.* 2017).

Natural capital is more common in economic literature, and is defined as "the stock of renewable and non-renewable resources that combine to yield a flow of benefits to people" (Natural Capital Coalition 2020). Natural capital refers to the stock of environmental amenities, for example air, plants, animals, geology and water. It is central to the ecosystem services framework, which places economic and non-economic value to natural resources (Daily *et al.* 2000). Underpinning the term natural capital is an assumption that the stock of natural resources is inexplicitly related to human health and well-being. Ultimately this valuation should enable decision-makers to better understand the complexities of the relationship between people and the natural environment (Natural Capital Coalition 2020).

Literature routed in the natural sciences such as ecology and biology, commonly uses definitions of the natural environment based on specific typologies of places and spaces. Examples of this include biodiversity as measured by bird species richness (Cameron *et al.* 2020), air quality as measured by levels of particulate matter ($PM_{2.5}$; Du *et al.* 2018), greenspace defined as vegetated land, and public greenspace defined as parks, gardens, woodlands and playing fields (Taylor & Hochuli 2017).

The natural environment is also subjectively experienced, and therefore will be valued differently across social and cultural contexts (Hartig *et al.* 2014; Kenter 2016; Pascual *et al.* 2017). Interestingly, the term nature appears to be preferred to biodiversity by the public (Campbell-Arvai 2019). It is clear that the interpretation of the natural environment differs across disciplines. Therefore, it is important for research to clearly define how the natural environment is being operationalised, and this is increasingly crucial as the need for future multidisciplinary work in this area grows (Taylor & Hochuli 2017).

1.3.1 Measures of the natural environment

To be able to examine the well-being effects of the natural environment, researchers must be able to define and measure aspects of the natural environment. The most common facets of the natural environment explored in well-being literature are greenspace (Mears *et al.* 2019a; Wheeler *et al.* 2015; White *et al.* 2019), bluespace (Bell *et al.* 2015a; Garrett *et al.* 2019b; Pasanen *et al.* 2019) and air quality (Ambrey *et al.* 2014; Laffan 2018; Mackerron & Mourato 2008; Welsch 2006). Others exist too, for example natural disasters such as flooding (Luechinger & Raschky 2009), weather and climate (Feddersen *et al.* 2016; von Möllendorff & Hirschfeld 2016), and noise (Brink 2011). However, these will not be discussed in this thesis.

Air quality

Air pollution is the largest environmental contributor to premature death and disease in the world today (Cohen *et al.* 2017). The European Environment Agency (EEA) defines air pollution as “the presence of contaminant or pollutant substances in the air at a concentration that interferes with human health or welfare, or produces other harmful environmental effects” (European Environment Agency 2017). There is a vast body of epidemiological literature which suggests that exposure to poor air quality has a substantive detrimental effect on physical health (Beelen *et al.* 2014; Brook *et al.* 2010; Brunekreef *et al.* 2015; Schraufnagel *et al.* 2019; Shah *et al.* 2015). For example, long-term exposure to air pollutants such as fine particulate matter ($PM_{2.5}$) and (PM_{10}), and other serious pollutants such as nitrogen oxide (NO_2), sulphur dioxide (SO_2) and ozone (O_3) has been associated with all- and natural- cause mortality (Beelen *et al.* 2014; Carey *et al.* 2013), and increased risk of cardiovascular disease (Shah *et al.* 2013) and lung cancer (Raaschou-Nielsen *et al.* 2013). There is also an emerging body of epidemiological research to suggest that air pollution may affect mental and cognitive health (Buoli *et al.* 2018; Power *et al.* 2016; Tzivian *et al.* 2015). Air pollution, caused predominantly from industrial output, fossil fuel combustion, road transport and household fuel burning, is a global public health issue and a current key target for global health policy (Cohen *et al.* 2017; Shah *et al.* 2013).

Air pollution has also been shown to have a negative relationship with subjective well-being. Studies have found this association with PM_{10} (Ambrey *et al.* 2014; Ferreira & Moro 2010; Levinson 2012), SO_2 (Ferreira *et al.* 2013; Luechinger 2009), and NO_2 (Du *et al.* 2018; Mackerron & Mourato 2008; Welsch 2002, 2006). For example, Mackerron and Mourato (2008) found a 10 $\mu g/m^3$ increase in NO_2 is associated with an average decrease of 0.5 across an 11 point scale of life satisfaction. However, some studies find nuances in their findings. For example, Zhang et al., (2017) use a combined index of pollutants to create a single measure of air quality in China, and find that poorer air quality reduces hedonic happiness and increases the rate of depressive symptoms, but there is little effect on life satisfaction. Krekel and MacKerron (2020) find no clear relationship between air pollution and momentary happiness in London, UK. There is much more research required to better understand the relationship and effect size between air pollution and subjective well-being.

Greenspace

A large proportion of literature on the relationship between human health and well-being and nature explores the physical and psychological impacts of exposure to greenspaces (Hoyle *et al.* 2019). Certainly in urban environments, the natural environment is most commonly referred to as greenspace (Ekkel & de Vries 2017). Benefits have been found in relation to a reduction in all-cause mortality and circulatory diseases (Mitchell and Popham, 2008), obesity (Astell-Burt *et al.* 2014b; Pereira *et al.* 2013), reduced anxiety and tension (Song *et al.* 2014), reduced mental fatigue (Park *et al.* 2011), birth outcomes (Dadvand *et al.* 2014), morbidity (Maas *et al.* 2009b) and better mental health in children and teenagers (Tillmann *et al.* 2018). Exposure to greenspace has also been linked to subjectively measured well-being benefits, such as increased self-reported happiness (Krekel & MacKerron 2020; White *et al.* 2017), increased self-reported vigour and vitality (Takayama *et al.* 2014), experiencing feelings of restoration (White *et al.* 2013c; Wyles *et al.* 2019), self-reported general health (de Vries *et al.* 2003; Wheeler *et al.* 2015), and improved mood (Tyrväinen *et al.* 2014).

However, there are also several studies that find weak or non-significant relationships between well-being and greenspace. For example, White et al., (2017) found no relationship between life satisfaction and three measures of nature exposure (neighbourhood greenspace, frequency of visits to natural places, and following a specific visit) in England. Pasanen et al., (2019) found no relationship between neighbourhood greenspace and self-reported general and mental health in England. Nutsford et al., (2016) found no relationship between self-reported psychological distress and views of greenspace in Wellington, New Zealand. Olsen *et al.* (2019) found a negative association between urban greenspace and life satisfaction across 66 European cities.

The term greenspace encapsulates a range of definitions itself, and there is still no universally accepted definition (WHO Regional Office for Europe 2016). Taylor and Hochuli (2017) conducted a review of health and well-being literature that researched 'greenspace', and found that the majority of papers did not provide a definition for greenspace. They found that the term was sometimes used to refer to places containing vegetation or 'natural surfaces', or places that have a particular use such as parks. In terms of urban greenspace, common definitions included public open spaces, such as parks, woodlands, children's playgrounds and community gardens; semi-public spaces such as allotments, golf courses, sports fields and wildlife reserves. Other types of urban greenspaces include private spaces, such as domestic gardens and green rooves. Sometimes streetscape features are included, such as street trees, road verges and railway embankments. Often bluespaces were found to be captured within the greenspace category, as well as grey or man-made surfaces, such as paths and public open squares.

Several studies use indices derived from satellite imagery to capture "greenness", such as NDVI or Enhanced Vegetation Index (EVI) from the MODIS instrument (de Keijzer *et al.* 2019; Kruize *et al.* 2020; Pereira *et al.* 2013). NDVI calculates the photosynthetic productivity of the land surface, therefore differentiating between what is vegetation and what is not, but also providing a suggestion of type and health of vegetation. However, these indices do not give detail on composition or characteristics of green spaces and provide no information about access rights. It is also difficult to differentiate between bluespaces and hard-standing surfaces using these indices and are therefore not used in the bluespace and well-being literature.

Bluespace

There is increasing recognition that, like greenspaces, bluespaces also provide health and well-being benefits (Foley & Kistemann 2015). Bluespace is broadly defined as any visible outdoor surface water (Britton *et al.* 2020). This includes rivers, lakes, reservoirs, coasts, and marine environments. Freshwater, coastal and marine environments have often been aggregated as part of green infrastructure, or even removed altogether, but studies now suggest that bluespaces provide different well-being benefits to greenspace, and that they may be realised through different mechanisms (Garrett *et al.* 2019b; Pasanen *et al.* 2019; Völker & Kistemann 2015).

Exposure to bluespaces has been associated with improved mental health (Pasanen *et al.* 2019), affect (White *et al.* 2010), self-reported general health (Garrett *et al.* 2019b; Wheeler *et al.* 2012; White *et al.* 2013a), recalled restoration (White *et al.* 2010, 2013c) and momentary happiness (Krekel & MacKerron 2020). It has also been related to lower levels of self-reported psychological distress (Nutsford *et al.* 2016) and number of reported symptoms (de Vries *et al.* 2003). Bluespaces have also been found to provide profound therapeutic and emotional experiences for individuals (Bell *et al.* 2015a).

However, other studies have found there to be no relationship between bluespace and well-being (Gascon *et al.* 2018; Mavoa *et al.* 2019a), while other studies have found inconclusive results (Dzhambov *et al.* 2018; Triguero-Mas *et al.* 2015). For example, no relationship was found between buffer bluespace and self-reported history of anxiety, depression and related intake of medicines (Gascon *et al.* 2018). Again, no relationship was found between proximity to coast or buffer blue space with subjective well-being in Victoria, Australia (Mavoa *et al.* 2019a).

Similarly with greenspace and well-being research, bluespace has also been categorised in different ways in the literature. In a review of bluespace literature, Gascon et al., (2017) found the majority of studies only examined non-inland bluespaces, such as coasts, beaches and saltwater zones. They also found that a small minority of studies examined only inland or freshwater bodies (e.g. rivers, lakes, reservoirs, canals and wetlands), but many combined both inland and non-inland water bodies into the same overarching bluespace category.

It is likely that coastal bluespace provides different well-being outcomes to inland freshwater environments. Much more research is needed to unpick the relationship between bluespace and well-being, including exploring subcategories and quality of bluespace, different well-being measures, and possible mechanisms (Britton *et al.* 2020; Mavoa *et al.* 2019a).

1.4 Types of green- and bluespaces

There have been recent calls for more research to identify the 'attributes' and 'types' of green- and bluespace that are associated with specific health benefits (Akpinar *et al.* 2016; Hartig *et al.* 2014; Wheeler *et al.* 2015). In the majority of studies to date, research has focussed on green/blue space as a homogeneous category, grouped together as one category 'open', 'natural', 'green' or 'blue' space (Olsen *et al.* 2019; Wheeler *et al.* 2015). One possible explanation for the nuance found in our current understanding of human well-being and nature could be in the different definitions and categorisations of open environments (Hunter & Luck 2015; Lai *et al.* 2019). Hunter & Luck, (2015) conducted a review to identify the greenspace typologies used in the literature and concluded that it is important to reflect the heterogeneity of urban greenspaces by using suitable metrics that reflect the ecological and social differences in natural sites. Very few studies use existing and consistent open space typologies to examine the relationship with well-being (Douglas *et al.* 2017).

Several studies address this by looking at the well-being effects of different land cover types within a residential neighbourhood. Wheeler et al., (2015) found a positive relationship between good self-reported general health (and a negative relationship with bad self-reported general health) and natural land cover types (broadleaf woodland, arable and horticulture, improved grassland, saltwater and coastal) and habitat diversity (Shannon's Diversity Index). In a study of rural residents in England, Alcock et al. (2015) found that living in coastal, mountain, agricultural and grassland environments was associated with better mental health (GHQ), however saltwater environments were negatively associated with mental health.

However, other studies find weak or mixed results. Bos et al., (2016) use the Dutch Land Use Database to find green space in The Netherlands. The database identifies land parcels as urban green (e.g. vegetable gardens, sports and recreation areas and parks), agricultural green and natural green, yet they group all of these categories together and refer only to green space. They found in the majority of their models a small or no significant relationship between green space and mental health. Triguero-Mas et al., (2017) used the Urban Atlas 2006 and the Top10NL land registry dataset to map green and blue space in four European cities. They group together urban green areas, agricultural/semi-natural/wetland areas, and natural forest/plantations to refer to green space, and water bodies as blue space. They also did not find any relationship with mental health. Akpinar et al., (2016) used one total green space category and five subcategories in the US National Land Cover Data (urban green space, forest, rangeland, agricultural land and wetland) to explore the effects on the number of mental health complaints in the last 30 days, anxiety-depression complaints in the last 2 weeks, and self-reported general health in a sample population in Washington State, USA. In urban areas they found no relationship between total greenspace and all three measures of well-being. They only found a significant association with mental health complaints and urban green space and forest cover, where zip-codes with increased urban green space and forest cover were related with fewer days of mental health complaints. There were no other significant relationships. Despite the positive relationship found in the study above, Wheeler et al., (2015) do not find any significant relationships with coniferous woodland, semi-natural grassland, mountain/heath/bog, or freshwater.

Other studies specifically examine trees and tree canopy. Reid et al. (2017) found residential proximity to trees more beneficial for self-reported health than proximity to grass. They also suggest that exposure to trees, particularly those outside of parks, may be particularly important for subjective health. In a study in London, UK, higher levels of street trees are associated with lower prescription rates of antidepressants (Taylor *et al.* 2015), and street trees and grass were both positively associated with psychological well-being in Ghangzhou, China (Wang *et al.* 2020).

Regarding bluespace, Gascon et al. (2017) conducted a systematic review of bluespace and well-being literature and concluded that only in a minority of studies do the authors differentiate between the coast and freshwater (or inland bluespace). For example, several studies using the UK Land Cover Map 2007 categories find differential relationships between residential proximity to the bluespace categories (saltwater, coastal and freshwater) and well-being in England. Wheeler et al., (2015) found positive associations with saltwater and coastal environments, but no relationship with freshwater. Alcock et al., (2015) found no relationship between mental health and freshwater environments, and a negative relationship with saltwater. Pasanen et al., (2019) found a positive relationship between mental health and residential freshwater in England. Additionally, proximity to the coast in England has been found to be beneficial for mental health and general health, but interestingly not life satisfaction (Garrett *et al.* 2019a; White *et al.* 2013a).

When studying the use of green- and bluespace, White et al. (2013c) found that visits to coastal, woodland and upland environments were associated with higher levels of reported restoration. Interestingly, when using a more detailed typology of land use categories, they found that visits to playing fields were less restorative than visits to open countryside. They also found that visits to many urban greenspace categories, such as town parks, were just as restorative as visits to open countryside (White *et al.* 2013c). In another English study, visits to rural and coastal greenspaces were more restorative than visits to urban greenspaces (Pasanen *et al.* 2019). MacKerron and Mourato, (2013) found positive associations with happiness and all nine natural land cover categories derived from the UK Land Cover Map 2007, when compared to continuous urban cover, using data collected from the Mappiness app in the UK. Allotment use has been associated with greater levels of physical activity and well-being, especially in older age (van den Berg *et al.* 2010b). Cameron et al., (2020) found a positive relationship between happiness and habitat diversity in parks in Sheffield, UK.

1.4.1 Domestic gardens

The relationship between well-being and private natural spaces is surprisingly under-researched. In the majority of studies, private or domestic gardens have either been aggregated into other greenspace categories (White *et al.* 2013b), assumed as part of the total surrounding greenness when using indices such as NDVI (Dadvand *et al.* 2014; Ekkel & de Vries 2017), or excluded completely from the analysis (Mitchell & Popham 2008; Nutsford *et al.* 2016).

Domestic gardens have been found to provide many health and well-being benefits to humans (Brindley *et al.* 2018; Cameron *et al.* 2012; Cox & Gaston 2016; de Bell *et al.* 2020b; de Vries *et al.* 2003). In a recent study in England, individuals with access to a private garden were more likely to report higher levels of life satisfaction than those who did not (de Bell *et al.* 2020b). They also found that those who had access to private outdoor space (patio, balcony etc) were more likely to meet physical activity guidelines (de Bell *et al.* 2020b). When adjusting for how private gardens are used (relaxing and/or gardening), they found that using the garden for relaxing only or gardening only was not associated with higher levels of life satisfaction. Gardening only was related to better self-reported general health. Using the garden for both relaxing and gardening was related to all five measures of health and well-being (life satisfaction, feeling their activities were worthwhile, general health, meeting physical activity guidelines, and visiting nature once a week). Interestingly, they found that private spaces were associated with health and well-being benefits, but access to communal gardens were not. This final finding is in contrast to Nielsen and Hansen (2007) who found that access to a garden or shared open space was positively associated with mental health (lower stress).

The well-being importance of private gardens compared to public green spaces has only been explored in a small handful of studies. Mavoa et al. (2019) found that access to a domestic garden (referred to as "greenness on private land") in urban areas of Melbourne, Australia, was more strongly positively correlated with subjective well-being than public greenspace. Dennis and James, (2017) found the proportion of an LSOA designated as domestic garden in north-west England has a greater effect size when mitigating poor health status than that of public green space. In The Netherlands, de Vries et al., (2003) found having a garden was associated with better mental health (measured by GHQ) but only for those individuals living in the very strongly urban municipalities. Additionally, upon adding the effect of surrounding greenspace into their model, the garden coefficient was not affected, indicating private gardens had a different well-being effect to public greenspace. de Bell et al., (2020) went further to show that in a representative population sample in England, those who had access to, and used, their private garden were more likely to visit public outdoor spaces than those who didn't.

All of these studies suggest that private open space in urban areas are equally or more significant to well-being than public open areas. Private open spaces are highly accessible in contrast to public open spaces which are less accessible and are not used by everyone (Mavoa *et al.* 2019a). Gardens provide direct and immediate opportunities to interact with nature (Cox & Gaston 2016), and represent an important part of urban green infrastructure.

Access to a domestic, and therefore private, garden may also influence the relationship between well-being and public natural environments. Gardens may be particularly important to individuals in large urban areas, where access to public natural spaces may be restricted. Or conversely, public open spaces may be particularly important to individuals in highly compact urbanised environments that do not accommodate large domestic garden sizes. Public natural spaces may offer different types of nature experience to a domestic garden (Shanahan *et al.* 2014). For example, experiences in a private garden may be solitary or even passive i.e. a view from a window (Coldwell & Evans 2018), or connected to activities such as gardening (Cameron *et al.* 2012; de Bell *et al.* 2020b), whereas public open spaces have been associated with increased social activity. Private spaces may also be associated with feelings of security and ownership (de Bell *et al.* 2020b). A better understanding of how private natural environments affect the relationship between wellbeing and public natural sites is required, particularly in urban environments where exposure to nature is limited.

1.5 Quality

Only a small handful of studies have attempted to capture quality characteristics of a natural environment that may affect how an individual receives well-being benefits. There have been recent calls for more studies examining the 'quality' of green and blue spaces (Nieuwenhuijsen *et al.* 2017; van den Berg *et al.* 2015).

Francis et al., (2012) found that objective measures of public open spaces in Perth, Australia, such as water features, birdlife and walking paths, have a strong relationship with mental health. Brindley et al., (2019) found green spaces with lower cleanliness levels were associated with higher prevalence of self-reported poor health in Sheffield, UK. Wheeler et al. (2015) use land use categories, bird species richness, water quality and protected area designation to represent quality of the natural environment in England, and find positive associations with subjective health for all but water quality. Wood et al. (2018) found that park amenity features and biodiversity measures are both positively related to psychological restorativeness in parks in Bradford, UK. Coombes et al., (2010) found 'formal green spaces' had higher visitation rates for physical activity in Bristol, UK, suggesting that this is because this category of natural space is characterised by a good path network and is well maintained. Wood et al., (2017) used a green space dataset for Perth, Australia to identify the number of recreation, sport and nature features contained within urban parks. They found a significant positive relationship between the number of features in parks within residential neighbourhoods and mental health.

Capturing the quality characteristics of natural environments that impact human well-being is difficult, and what is perceived as *quality* could be largely subjective. This has been found in literature that assessed how perceived quality relates to well-being. Pretty et al., (2005) found greater restorative benefits from environments perceived as pleasant (i.e. clean, aesthetically pleasing). Ayala-Azcárraga et al., (2019) found that the perceived height of trees and perceived presence of bird song were the best environmental variables of parks in Mexico City to predict subjective well-being of visitors. In the same study, perceived cleaning, illumination and exercise facilities predict the possibility of sites being visited (Ayala-Azcárraga *et al.* 2019). Garrett et al., (2019) found that perceived safety and perceived presence of wildlife were associated with recalled well-being following a visit to blue space for residents in Hong Kong. However, perceived safety and litter were not. Perceived good facilities and wildlife were associated with intentional exposure to blue spaces (Garrett *et al.* 2019b). However, Akpinar (2016) also interviewed individuals to capture perceived green space quality, using questions relating to aesthetic, cleanliness, maintenance, largeness, shaded areas, lights, and openness/visibility. They found only largeness and openness/visibility were related to improved mental and physical health. Zhang et al., (2017) used accessibility and usability of green spaces to infer quality, and an additional six-item instrument in a questionnaire to elicit perceived quality by residents. They found neither of these measures to be associated with well-being, although they suggest that they impact well-being by improving levels of neighbourhood satisfaction. Annerstedt *et al.* (2012) also did not find a significant relationship between eight “gold standard” green qualities (serene, wild, lush, space, the common, the pleasure garden, and festive and culture) and well-being in Sweden.

1.5.1 Biodiversity

There is evidence to suggest that the ecological quality or biodiversity of urban natural spaces are important indicators of quality of a site, with more biodiverse environments related to higher levels of health and well-being (Cameron *et al.* 2020; Clark *et al.* 2014; Lovell *et al.* 2014; Luck *et al.* 2011). For example, Cameron et al., (2020) found a positive relationship between both avian biodiversity and habitat diversity with the self-report happiness of visitors in greenspaces in Sheffield, UK. Wood et al., (2018) found park biodiversity measures, such as species richness, habitat diversity and tree canopy cover, were positively related to psychological restorativeness in parks in Bradford, UK. Lindemann-Matthies and Matthies, (2018) found a positive association between plant species richness and stress levels of park visitors in Zurich, Switzerland.

However, studies examining the relationship between neighbourhood biodiversity and well-being find mixed results. Luck et al., (2011) found a positive relationship between vegetation cover and subjective wellbeing, but only a weak positive relationship with bird species richness and abundance. Fuller et al., (2007) found inconsistent relationship between biodiversity metrics and three psychological well-being measures in Sheffield, UK. They found plant species richness, and to a lesser extent bird species richness, to be related to at least two measures of well-being. However butterfly species richness and tree canopy cover had no association with any well-being measures. Taylor et al., (2018) found an association between general well-being and NDVI (mean and standard deviation, the latter as a proxy for biodiversity) in Australia but not for bird species richness, and the association only occurs in two of their four study cities. Wheeler et al., (2015) found a positive relationship with bird species richness but no negative relationship with bad self-reported general health. Dallimer et al., (2012) found plant, bird and butterfly species richness measures had inconsistent correlations with psychological well-being in Sheffield, UK. They found a positive relationship with bird species richness, a negative relationship with plant richness, and no relationship at all with butterfly richness.

The inconclusive findings in the literature to date may be partially explained by the biodiversity measures used. Previous studies measure biodiversity in a number of ways, by using objective scores of species richness (Cameron *et al.* 2020; Luck *et al.* 2011), habitat diversity (Cameron *et al.* 2020; Schebella *et al.* 2019), vegetation cover (Dallimer *et al.* 2012; Luck *et al.* 2011), NDVI (Mavoa *et al.* 2019a) or protected area status (Wheeler *et al.* 2015; Wyles *et al.* 2019), and subjective scores such as perceived biodiversity (Dallimer *et al.* 2012; Schebella *et al.* 2019). Often particular taxonomic groups are selected to study, such as birds (Cameron *et al.* 2020; Dallimer *et al.* 2012, 2014; Fuller *et al.* 2007; Luck *et al.* 2011; Schebella *et al.* 2019; Taylor *et al.* 2018; Wheeler *et al.* 2015), butterflies (Fuller *et al.* 2007), and plants (Fuller *et al.* 2007; Luck *et al.* 2011). One study used four measures of insect biodiversity, richness, abundance, diversity and evenness, but found no effect on physiological well-being measures (Chang *et al.* 2016). Biodiversity data also contains known biases, such as observer bias and identification bias (slower, brighter, bigger species easier and more interesting to identify), and problems of often being presence only data with rarer and small species being difficult to observe (Isaac & Pocock 2015). However, arguably these more easily observed species will be more likely perceived by the public so more likely to influence well-being.

Perceived biodiversity may be more important for individual well-being than objective biodiversity metrics. For example, Schebella et al., (2019) found that perceived biodiversity of urban greenspaces in South Australia were better predictors of subjective well-being measures than objectively measured biodiversity. Certainly evidence suggests perceived species-richness is a suitable proxy for measured species-richness (Southon *et al.* 2018). However this relationship has been disputed, and called the people-biodiversity paradox (Pett *et al.* 2016). This describes there being a mismatch between people's biodiversity preferences and how they relate to their well-being, and people's ability to accurately perceive biodiversity levels. It is likely that the relationship between biodiversity and well-being is personally, socially, and culturally dependent (Pett *et al.* 2016) and that the beliefs and perceptions held by individuals will affect the well-being impacts of exposure to greenspace (Marselle *et al.* 2015). For example, studies have found the relationship between biodiversity and well-being may be mediated by perceived restoration (Carrus *et al.* 2015; Marselle *et al.* 2015), or nature connectedness (Cox *et al.* 2017) or eco-centricity (Southon *et al.* 2018).

It is reasonable to suggest that natural environments with higher levels of biodiversity should provide more health benefits to humans than those of lower biodiversity levels but the evidence is not robust (Lovell *et al.* 2014). One suggestion is that higher biodiversity levels indicate a more robust ecosystem, providing ecosystem services that improve well-being (Aerts *et al.* 2018; Millennium Ecosystem Assessment 2005). Another is that more biodiverse environments provide increased opportunities for interacting with nature, which has restorative psychological and physiological benefits (see Marselle, 2019 for a full review). However, research indicates that while sites that support higher levels of biodiversity are likely to be larger, less fragmented and considered more 'wild' (Ayala-Azcárraga *et al.* 2019), this urban structure in fact limits human access and use, and therefore the potential for individuals to gain well-being benefits from them (Jennings *et al.* 2017). Gaining a better understanding of how biodiversity affect well-being will be important to informing future green/blue space planning.

1.5.2 Protected status

An alternative measure for biodiversity is the protected designation of a site. Designation of a site implies a level of significant natural importance and biodiversity. Wheeler et al. (2015) use protected area designation, as well as land use categories, bird species richness, water quality, to represent quality of the natural environment in England. They use common designations in the UK as their protected areas layer (Sites of Special Scientific Interest, Special Areas of Conservation, Special Protection Areas, Local Nature Reserves, National Nature Reserves and Ramsar designated wetlands). Protected designation implies a level of ecological quality and they find positive associations between proximity to protected sites and self-reported good health, and similarly negative associations with self-reported bad health. Wyles et al., (2019) find protected designation status of a green or blue space is associated with greater psychological restoration and feeling more connected to nature. Pasanen et al., (2019) found that visits to urban and coastal greenspaces were more restorative when the site had protected status for adults in England, however this was not significant for rural greenspaces. The use of protected status of a site to suggest ecological quality is interesting, particularly given the problems related to measuring biodiversity effectively for well-being relationships.

1.6 Pathways to benefits/disbenefits

There have been several suggested mechanisms through which these benefits may be realised, that sit under three general functions of green- and bluespaces: reducing harm, restoring capacities and building capacities (Markevych *et al.* 2017). Reducing harm refers to mitigating or protecting functions to protect against exposure to environmental 'bads', such as air pollution (Dadvand *et al.* 2015; Laffan 2018; Sheridan *et al.* 2019; Tallis *et al.* 2011; Yuan *et al.* 2018), heat (Bowler *et al.* 2010) and noise (Gascon *et al.* 2018). Restoring capacities relates to the restorative experience of exposure to nature for example by reducing levels of objective and perceived anxiety and stress. Possible mechanisms suggested include the Biophilia Hypothesis, Attention Restoration Theory (ART) and Stress Reduction Theory (SRT). Building capacities refers to the functionality of greenspace that encourages activities and behaviours relating to physical activity and exercise, and increasing social contact time and social activities.

1.6.1 Reducing harm

Several studies explore the role of greenspaces in reducing air pollution, as a mechanism for explaining the well-being benefits gained from cleaner air. Wang et al., (2020) found that $PM_{2.5}$ and NO_2 both mediated the positive relation between streetscape greenery and psychological mental health in Ghangzhou, China. However neither mediated the positive relationship between NDVI and psychological mental health. Gascon et al., (2018) found air pollution ($PM_{2.5}$ and NO_2) only partially mediated the negative relationships found between residential greenspace and self-reported depression and intake of related medicines. Laffan (2018) found that frequency of visits to natural environments partially mediates the negative relationship between air pollution and life satisfaction. O_3 has a different pattern to other pollutants; it recombines with NO thus decreasing O_3 levels. Therefore, it is possible to find higher O_3 levels in greenspaces (Bowler *et al.* 2010).

It is possible that air pollution is both a confounder and a mediator in the pathway from greenspace to health (Klompmaker *et al.* 2019). Air pollution as a mediator sees greenspace reducing levels of air pollution by creating a buffer or through absorption and dispersal, whereas air pollution as a confounder may mean that in greener areas there are fewer pollution sources.

Green- and bluespaces have also been shown to buffer against noise and urban heat (Dadvand & Nieuwenhuijsen 2019), and there is some evidence to suggest biodiversity supports a diverse human gut microbiome and therefore protects against disease (Aerts *et al.* 2018; Hough 2014; Lai *et al.* 2019; Pearson *et al.* 2020). While this research suggests a plausible benefit pathway between the condition of the natural environment and human health, there are very few studies that explore this, and the evidence base is still emerging.

1.6.2 Restoring capacities

The term 'biophilia' was first described by E. O. Wilson in 1984 to describe literally "the love of life", how humans have an innate attraction to nature. The theory was furthered in Kellert & Wilson (1993) to describe the Biophilia Hypothesis, how in an evolutionary sense humans' affiliation with nature has allowed mankind to survive and thrive within the landscape. This concept has received much recent attention, and is synonymous with phrases such as nature connectedness (Capaldi *et al.* 2014) and nature relatedness (Nisbet *et al.* 2010). Nature connectedness refers to an emotional or spiritual response to nature and is fundamentally different to simply engaging with natural beauty, although both are associated with increased levels of well-being (Zhang *et al.* 2014).

SRT and ART are complimentary in that they both bring about a restorative feeling to a person, but they differ because ART is psycho-functionalist and SRT is psycho-evolutionary theory (Berto 2014). ART theory suggests that exposure to natural environments requires lower levels of cognitive directed (or voluntary) attention than in unnatural environments, and therefore allows the associated areas of your brain to rest (Aspinall *et al.* 2015). Urban areas require higher levels of direct attention due to increased levels of stimuli such as advertising, traffic lights and cars. Natural environments allow this directed attention to rest or restore and therefore a person is much more able to focus and provide directed attention following a period of time in nature.

ART was first defined by Kaplan & Kaplan (1989) has been suggested as a key benefit of exposure to nature through the reduction of mental fatigue (Berman *et al.* 2008; Felsten 2009; Kaplan 1995). ART also allows for an individual to 'clear their mind', gain cognitive peace and to reflect more deeply on life (Roe & Aspinall 2011). Berman *et al.* (2008) found that participants were more able to recall numbers in the digit-span task after interactions with nature as opposed to urban areas. This was irrespective of mood and season. They also showed that participants found pictures of nature more refreshing and enjoyable than those of urban areas. They concluded that experiences with nature (either physically being present in nature or simply looking at pictures of nature) lead to improved directed attention ability. Improvements in physical health have been reported when hospital rooms have a view of green spaces (Ulrich 1984). Views of forest environments in Japan (Takayama *et al.* 2014). However, a systematic review of ART studies concluded that research in this area needs to better articulate and operationalise how attention is defined and measured, to be able to better draw consensus across studies (Ohly *et al.* 2016).

The Stress Reduction Theory (SRT) (sometimes called the Psycho-physiological SRT) differs from ART in that it is a physiological response as opposed to a mental one. It describes how in evolutionary terms humans are akin with nature and this brings about a physical calming via the body's limbic system (Berto 2014; Bird 2007). Indeed stress as a condition is mediated by psychological processes so the two theories are not mutually exclusive (Tyrväinen *et al.* 2014). Cortisol levels are one of the main physiological responses to stress and decreased levels following exposure to greenspace have been measured in several studies (Roe *et al.* 2013; Tyrväinen *et al.* 2014). Green environments have been linked to lower heart rates (Laumann *et al.* 2003), decreased blood pressure (Hartig *et al.* 2003) and higher levels of perceived health (Maas *et al.* 2006). Stress has been found to be a significant mediator in the positive relationship between greenspace and mental health (de Vries *et al.* 2013; Triguero-Mas *et al.* 2017) and partially for perceived general health (de Vries *et al.* 2013).

1.6.3 Building capacities

Nature has been found to promote opportunities for recreation and physical activity and therefore is intrinsically linked with improved physical health (Akpinar 2016; Barton & Pretty 2010). Despite these positive findings, other studies find nuanced results, greenspaces promoting physical activity for dog walkers only (White *et al.* 2018), differential relationships dependent on greenspace definitions and access metrics (Klompmaker *et al.* 2018). Some find no relationship at all (Triguero-Mas *et al.* 2015). Physical activity has been found to only partially mediate the relationship between greenspace and health (de Vries *et al.* 2013; Richardson *et al.* 2013). Reviews have concluded that evidence to show an association between access to greenspace and physical activity is inconclusive (Lachowycz & Jones 2011).

Green exercise has also been shown to be more mentally beneficial than that conducted in unnatural environments (Annerstedt *et al.* 2012; Mitchell 2013; Pretty *et al.* 2005; Roe & Aspinall 2011). Although the type or 'severity' of physical activity seems to be important (Pasanen *et al.* 2019) as does the quality of the natural environment (Annerstedt *et al.* 2012; Schipperijn *et al.* 2013). Indeed the contradictory findings above may be explained by physical activity being an insignificant mediator in the relationship between greenspace and health. De Vries et al., (2013) suggests that the health benefits gained from conducting physical activity in natural places is due to the restorative nature of the environment, and not the activity itself.

Social interactions and a sense of community belonging have been associated with improved health and well-being, and greenspaces have been shown to foster opportunities for increased social activity (Kruize *et al.* 2020). Maas et al. (2009a) reported both better perceived health and higher levels of neighbourhood greenness were related to lower reported loneliness and higher levels of social contacts in their network. They found that both measures of social cohesion partially mediated the positive relationship between neighbourhood greenspace and self-reported health. Social cohesion therefore may act as a potential mediator between greenspace and well-being. Fan et al. (2011) found that urban parks indirectly mitigated stress by fostering social support. De Vries et al. (2013) found that social cohesion was a strong mediator of the positive relationship found between streetscape greenery and a range of physical and mental health measures. Despite finding no direct relationship with residential green- and/or bluespace, Rugel et al. (2019) found sense of community was positively related to increased natural space (a combined metric of green- and bluespace). Certainly urban environments have been linked to specific social stress processing in the brain (Lederbogen *et al.* 2011).

Social cohesion has several definitions itself and is multi-faceted. It encompasses feelings of trust, support, a sense of community and belonging (de Vries *et al.* 2013; Forrest & Kearns 2001). It may be that different measures of social cohesion capture different aspects of how the natural environment brings about well-being, through social connectedness, social capital and social support (Carpiano & Hystad 2011). Indeed, to the contrary of positive feeling of social cohesion, certain studies find negative responses to urban greenspace, related to incidents of antisocial behaviour such as crime (Lorenc *et al.* 2013) and related to feelings of unsafety around other people (Finlay *et al.* 2015).

The pathways to well-being benefits are context-specific and likely to overlap and connect. For example, allotments have been shown to be particularly beneficial to older adults in terms of social cohesion and physical activity. Urban public parks have been found to be particularly important for opportunities for physical activity. Visits to freshwater spaces have been found to be more psychologically beneficial when nature was considered important to the visit (de Bell *et al.* 2017).

1.7 Exposure

In research that examines the health and well-being effects of the natural environment, there are two key methods that are used to operationalise exposure: a) “residential” exposure, and “visit/use” exposure (White *et al.* 2017). Of course they are inextricably linked; for example, the likelihood and frequency of visiting a green or blue space increases with residential proximity (Ekkel & de Vries 2017; Elliott *et al.* 2020; White *et al.* 2013c). Capturing exposure to outdoor air pollution in individual well-being literature is inherently different to that of green- and bluespaces. Green- and bluespaces arguably have discrete boundaries enabling the calculation of a range of proximity and exposure methods. Air pollution is not discrete, and therefore can effectively be measured anywhere in space. In nearly all air pollution and well-being literature, residential exposure is used. In this thesis, I will focus on residential exposure only.

Evidence suggests that greenspace surrounding an individual's residence is beneficial for health and well-being (de Vries *et al.* 2003; Mitchell & Popham 2008; van den Berg *et al.* 2015; Wheeler *et al.* 2015). For example, higher levels of residential greenspace have been associated with higher levels of life satisfaction (Mavoa *et al.* 2019a; White *et al.* 2013b), a reduction in all-cause mortality and circulatory diseases (Mitchell and Popham, 2008), self-reported general health (de Vries *et al.* 2003; Wheeler *et al.* 2015). High levels of residential greenspace during childhood are also associated with a lower risk of developing psychiatric disorders in adolescence and adulthood (Engemann *et al.* 2019). The relationship is not specific to urban settings, a positive relationship between greenspace and well-being has also been found in rural areas too (Alcock *et al.* 2015).

Similarly, residential proximity to bluespace has also been associated with well-being benefits. For example, residential views of blue space have been found to be related to lower levels of self-reported psychological distress in Wellington, New Zealand (Nutsford *et al.* 2016). Proximity to coast and residential freshwater coverage have been found to be associated with better mental health in England (Pasanen *et al.* 2019). Living within 5km of the coast in England was associated with better mental health (GHQ) and self-reported general health (White *et al.* 2013a). A higher proportion of bluespace in a residential 1km buffer was found to be associated with better self-reported mental and general health and lower levels of mood and anxiety disorders, with the effect sizes larger than that for greenspace (de Vries *et al.* 2016).

Intuitively the relationship between residential green- and bluespace and well-being makes sense. The likelihood of visiting natural spaces has been found to increase with proximity to green spaces (White *et al.* 2013c) and blue spaces (Elliott *et al.* 2020). In small parks in Mexico City, visitors were predominantly from the local neighbourhood (Ayala-Azcárraga *et al.* 2019). Dallimer et al., (2014) found that time taken to reach greenspaces was one of the most important factors in explaining frequency of visits to urban greenspaces in Sheffield, UK. This is important because it has been shown that the frequency and duration of exposure dose to greenspace are related to the health benefits felt by individuals in urban and suburban areas (Cox *et al.* 2018), so if natural sites are close by and easy to reach, individuals are much more likely to visit and gain well-being benefits from them.

Keniger et al., (2013) identified three broad ways that individuals will interact or experience green- and bluespace: indirect interactions (viewing nature from a window), incidental interactions (interacting with nature as a consequence of another activity) and intentional interactions (direct intent to experience nature). Residential greenspace supports all three of these methods: the 'indirect' (e.g. view from a residential window), the 'incidental' exposure domain, where natural environments are accessed as a by-product of other activities, such as commuting, as well as the 'intentional' too (i.e. more likely to visit if in close proximity).

However, amount of residential natural space does not fully capture use of that space, or also any use of natural space outside of the neighbourhood (White *et al.* 2019). Those living in neighbourhoods with low greenspace coverage were actually found to have higher odds of achieving >120minutes recreationally visiting greenspaces (White *et al.* 2019). This suggests that individuals can also be exposed to natural environments in other ways, such as through visits to greenspaces outside of their neighbourhood, such as in another part of the city or by visiting the countryside or coast (Ayala-Azcárraga *et al.* 2019).

The same applies with air pollution. While residential values of air pollution are accepted as capturing exposure, exposure when away of the home is not captured. Exposure at place of work, while commuting, and at places of leisure activities are not accounted for. Similarly, indoor air pollution is not captured.

1.7.1 Methods for measuring residential exposure

There are two key types of air pollution data used in health and well-being literature, modelled and observed (Ambrey *et al.* 2014). Observed air pollution uses data recorded at air pollution measurement stations (e.g. Ferreira et al., 2013; Levinson, 2012; Luechinger, 2009). Modelled air pollution data accounts for the effects of distance from pollution sources and measurement stations, weather conditions and dispersal (e.g. Ambrey et al., 2014; Laffan, 2018; Mackerron and Mourato, 2008). Using observed data from measurement stations has been criticised when attributing the data to individuals, as the distance between the nearest station and residential location maybe large, therefore increasing measurement error (Dibben & Clemens 2015). Modelled data has the benefit that small area estimates can be produced, taking into account several measurement stations and local prevailing conditions.

Ekkel & de Vries (2017) provide a comprehensive review of proximity and access metric issues in the greenspace and health literature, and the same issues presumably apply with bluespace access too. Ultimately they highlight the need for improved methods for capturing how individuals are exposed to natural environments. Most studies use simple proximity metrics to capture residential exposure to natural environments, such as presence in, or proportion of, radial buffer zones (Kruize *et al.* 2020; Maas *et al.* 2009a; Triguero-Mas *et al.* 2017; Wood *et al.* 2017), administrative boundaries (Akpinar *et al.* 2016; Ambrey & Fleming 2013; Astell-Burt *et al.* 2014c; Wheeler *et al.* 2015; White *et al.* 2013b), or by using Euclidean distance to a site edge (Dzhambov *et al.* 2018; Gascon *et al.* 2018; Krekel *et al.* 2016; Kruize *et al.* 2020). Jarvis et al., (2020) have recently redefined access, by subdividing residential access to green- and bluespace into "access" and "exposure". Here, access is measured by a distance value between residential location and a particular natural space entity, and exposure is measured as a proportion of the surrounding neighbourhood or buffer for example. They found that across the urban-rural gradient in Metropolitan Vancouver, access and exposure were only weakly correlated. While access (defined as living within a 300m walk of a natural space of size $\geq$1 ha) remained relatively constant, exposure increased with distance from the city centre.

Administrative boundaries, such as districts, postal units, and in the UK, lower super output areas (LSOAs), provide convenient units for calculating averaged statistics across the unit. Metrics are calculated as percentages of unit area, and are useful when used alongside other supporting variables which are available at this level, such as neighbourhood deprivation and population density. Generally they are bounded by population size, for example English and Welsh LSOAs have between 1000-3000 residents each. Therefore LSOAs in more urbanised areas are much smaller in area than rural ones. This has implications for national research as the amount of land area assigned to each individual will vary quite significantly. The same applies in the US, where urban zipcodes are bounded by 1000 residents and above, and rural as below 1000 residents. A useful method could be subdividing rural units further, as found in Akpinar et al. (2016). In the literature, buffers zones about a point, perhaps an exact postcode location or a centroid of a larger unit, are also common. Buffers and Euclidean distances are arguably more useful than administrative boundaries as they may provide a more realistic representation of how an individual uses their local surroundings. However both methods do not necessarily consider issues of access, as they do not account for potential barriers such as railway lines, or sites being closed for public use.

To address this issue of access, an alternative proximity measure to buffers and administrative units is travel time/distance often referred to as network buffers or service areas (Browning & Lee 2017). This network analysis approach uses known travel routes (e.g. road networks) to generate buffers/service areas that represent the total area that an individual could reach by road given a certain distance, intending to better represent how an individual moves through their local area. For example, a common approach is to create areas around each individual's residence based on a 1.6km (1 mile) road network (Astell-Burt & Feng 2019; Pereira *et al.* 2012, 2013). This approach is less common presumably as it requires a large processing effort and access to a highly detailed and spatially resolved data regarding routes and access points. Again, this method does not account for access rights, or other walking routes such as paths and alleyways.

However, the use of buffers and network buffers suffer from the same issue: there is no widely-recognised 'standard' for which buffer size to use (Houlden *et al.* 2018; Labib *et al.* 2020a). Current understanding of optimal distance is currently based on expert opinion (Browning & Lee 2017), and this differs across nations. The size of buffers used in the literature often represents arbitrary Euclidean distance values assumed by the researcher or based upon national policy guidance. For example, in the US it is suggested that greenspace within a five minute walk (or 320m) are important or physical health (Browning & Lee 2017). In Europe, the European Commission's recommendation that public open spaces should be within 300m of an individual's residence is frequently cited (Labib *et al.* 2020b), and within a 300m linear distance and a minimum greenspace size of 1 hectare is also proposed (Annerstedt Van Den Bosch *et al.* 2016). In the UK, Natural England also recommends a 300m Euclidean distance. In the literature, buffer sizes vary from 100-3000m (

Table 1.1).

Table 1.1. Different buffer sizes used in literature that studies the relationship between health and well-being.

Buffer size	Reference
100m	(Dzhambov *et al.* 2018; Gascon *et al.* 2018; Reid *et al.* 2018; Rugel *et al.* 2019; Triguero-Mas *et al.* 2015)
250m	(Rugel *et al.* 2019; Wang *et al.* 2019)
300m	(Annerstedt *et al.* 2012; Dzhambov *et al.* 2018; Gascon *et al.* 2018; Kruize *et al.* 2020; Reid *et al.* 2017, 2018)
350m	(Wang *et al.* 2019)
400m	(Rugel *et al.* 2019)
450m	(Wang *et al.* 2019)
500m	(de Keijzer *et al.* 2019; Dzhambov *et al.* 2018; Gascon *et al.* 2018; Reid *et al.* 2018; Rugel *et al.* 2019; Triguero-Mas *et al.* 2015)
550m	(Wang *et al.* 2019)
650m	(Wang *et al.* 2019)
750m	(Wang *et al.* 2019)
850m	(Wang *et al.* 2019)
950m	(Wang *et al.* 2019)
1000m	(Astell-Burt *et al.* 2014a; Bos *et al.* 2016; de Keijzer *et al.* 2019; de Vries *et al.* 2016; Maas *et al.* 2009a, 2009b; Reid *et al.* 2017, 2018; Rugel *et al.* 2019; Triguero-Mas *et al.* 2015; van den Berg *et al.* 2010a)
1600m	(Astell-Burt & Feng 2019; Pereira *et al.* 2012, 2013)
2000m	(Reid *et al.* 2018)
3000m	(Bos *et al.* 2016; Maas *et al.* 2009a, 2009b; van den Berg *et al.* 2010a)

Often, studies use several buffer sizes for testing hypothesis and for sensitivity testing (Labib *et al.* 2020b). Small buffer distances have been described as representing green- and bluespace that is easily accessible and may be seen from the home. Larger buffers are connected with likely maximum walking distances. 300m has been described as representative of one's neighbourhood (Annerstedt *et al.* 2012). Several studies now recommend that when using multiple buffer distances that they should be nested rather than overlapping, to differentiate between natural environments that are considered close to the centroid and those that are further away (Browning & Lee 2017).

Larger buffer sizes associated with better self-reported health outcomes (Browning & Lee 2017; Reid *et al.* 2018; Su *et al.* 2019). In a review of buffer size and physical health outcomes, Browning and Lee (2017) found that this relationship held, with increasing numbers of studies reporting health benefits, until the buffer size exceeded 1999m. Smaller buffer sizes have been found to be important for mental health. The 350m buffer was the optimal buffer radius for lowest odds of serious psychological distress in Californian teenagers, although there was little evidence for this relationship in adults (Wang *et al.* 2019). Residential NDVI in a 300m buffer had a significant association with mental health in Plovdiv, Bulgaria (Dzhambov *et al.* 2018). Yet Bos et al., (2016) found a relationship between better mental and surrounding greenspace in a 3km, but not 1km, buffer in The Netherlands. Similarly, also in The Netherlands, respondents with high residential greenspace in a 3km buffer were found to be less affected in their self-reported general and mental health by stressful events than those with a low amount of greenspace, and this relationship was not significant for 1km buffers (van den Berg *et al.* 2010a). Regardless of distance, the use of discrete boundaries (buffers or neighbourhoods) does not allow the study to test for distance-decay effects through space (Labib *et al.* 2020b), and therefore simplifies the spatial landscape and relationship between units.

The access or exposure method used greatly depends on how the natural environment is being represented in the study. Common datasets include land cover/use databases, field survey results and remotely sensed vegetation indices such as NDVI. Land cover and land use datasets are GIS databases that generally are created from remotely sensed classification data and/or field surveys, collected at the regional, national or international level. For the purposes of nature-well-being research, vector databases will provide the location, size and characteristics of land parcels. Raster datasets will provide grid cell values relating to different land use/cover categories. Examples of those used in the literature include the UK Land Cover Map (Alcock *et al.* 2015; Wheeler *et al.* 2015), the US National Land Cover Database (Akpinar *et al.* 2016), the European CORINE land cover dataset (Annerstedt *et al.* 2012; Triguero-Mas *et al.* 2015), Map of Land Covers of Catalonia (Gascon *et al.* 2018), Dutch Land Use Database (Bos *et al.* 2016), Urban Atlas 2012 (Dzhambov *et al.* 2018; Kruize *et al.* 2020), Tree Cover Density map 2012 (Dzhambov *et al.* 2018). These datasets can also be summarised to common administrative units for governmental reporting. A commonly used example of this is the Generalised Land Use Database (GLUD) for England (Alcock *et al.* 2014; Mitchell & Popham 2008; White *et al.* 2013b, 2018).

Many studies that examine bluespace look at coastal bluespaces. Exposure to this is usually measured as the Euclidean distance to the coast (Brereton *et al.* 2008; Wheeler *et al.* 2012; White *et al.* 2013a). Inland bluespaces are usually obtained from land use land cover datasets, and these are measured as Euclidean distance to nearest water body (Dzhambov *et al.* 2018), proportion cover in buffer/neighbourhood (Rugel *et al.* 2019), or simply presence/absence in areal unit (Dzhambov *et al.* 2018; Rugel *et al.* 2019; Triguero-Mas *et al.* 2015). Bluespaces create negative NDVI values and therefore make the calculation of mean scores within a boundary (e.g. buffer or neighbourhood) inaccurate (Ekkel & de Vries 2017). Therefore in most studies, these are removed from the analysis, despite potentially having important and different well-being effects. Indeed, in some studies bluespaces are added again from an alternative data source, such as the Open Street Map water layer (Dzhambov *et al.* 2018) or a land cover land use database (Rugel *et al.* 2019).

Methods that use satellite imagery to capture the ”greenness” of a site, such as the Normalised Difference Vegetation Index (NDVI) or the Enhanced Vegetation Index (EVI) from the MODIS instrument, provide a measure that suggests a range of type and health of vegetation in an area. This has been used in various studies to explore the association between health and well-being and the natural environment (Gascon *et al.* 2018; Mavoa *et al.* 2019a; Pereira *et al.* 2013; Reid *et al.* 2018; Sarkar *et al.* 2018; Su *et al.* 2019; Taylor *et al.* 2018; Triguero-Mas *et al.* 2015, 2017). The benefit of using these greenness indices is that they can be derived from freely available imagery, and for relatively large land areas, and for multiple years. The data is continuous, there are no gaps, and they capture ‘greenness’ on private land such as domestic gardens, which is often omitted from studies exploring the relationship between health and the natural environment. They also do not suffer from the issues affecting studies using land use categories, in that the scale is consistent across space. Land use categorisation differ from place to place which makes a comparative analysis impossible. However these indices do not give detail on composition or characteristics of green spaces and provide no information about access rights. It is also difficult to differentiate between bluespaces and hard-standing surfaces using these indices and are therefore not used in the bluespace and well-being literature.

Compounding the issue of distance and buffer size/walking distance/administrative boundary size, is that of spatial scale of the green- and bluespace data. Data sources have different resolutions and types (Labib *et al.* 2020b). Vector land use/cover datasets have a minimum unit limit due to the limitation of remotely sensed imagery classification to detect items that are smaller. The minimum unit is 25ha in CORINE Land cover 2006 (Triguero-Mas *et al.* 2015) 0.5ha in the Dutch Land Use Database (Bos *et al.* 2016). Therefore, it is likely that smaller green- and bluespaces are not captured in these datasets. Additionally, greenness indices such as NDVI or raster land use layers are built on pixel sizes, and these remotely sensed images are taken from instruments with different resolutions. For example, Landsat 7 and 8 have a 30m pixel size (Dzhambov *et al.* 2018; Kruize *et al.* 2020; Reid *et al.* 2018; Triguero-Mas *et al.* 2015), whereas Sentinel 2 is 10m (Dzhambov *et al.* 2018). MODIS is 250m (Reid *et al.* 2018; Rugel *et al.* 2019; Wang *et al.* 2019). DigitalGlobe's Worldview 3 satellite is 2m (Astell-Burt & Feng 2019). AVHRR is 1000m resolution (Reid *et al.* 2018). Therefore, the US National Land Cover Database is classified using Landsat imagery so has a 30m resolution (Akpinar *et al.* 2016). For smaller green- and bluespaces, it is likely that these are misclassified in these datasets with lower spatial resolutions. It is likely that coarser data products are used due to them being widely and freely available. Products of higher spatial resolution have tended to be costly or more spatially discrete.

The inherent spatial nature of the relationship between well-being and the natural environment has led to GIS techniques being the most common methods for representing data and calculating proximity and exposure. Therefore in all methods used to aggregated or bound both phenomena by spatial units leads to the Modifiable Areal Unit Problem (MAUP) which has implications for health outcomes (Labib *et al.* 2020b). The size and shape of the buffer/neighbourhood will capture different measurements of the natural environment, and the resolution or aggregation of the environmental dataset needs to be appropriate for the proximity/accessibility measure. Various studies have used a range of buffer sizes with a range of greenspace datasets at differing spatial resolutions to explore this issue (Reid *et al.* 2018; Su *et al.* 2019). A recent study suggested buffer size limits when using Sentinel2 (approx. 640m) and Landsat (approx. 480m) imagery, beyond which urban greenspace characteristics are no longer properly captured as they are over-aggregated (Labib *et al.* 2020a)

The spatial dimension used is important because it will inherently reflect a different set of green- and bluespace metrics. In a systematic review, Labib et al., (2020b) found that the different types of approaches used to define and capture accessibility, and the size of those units, influence the strength and significance of associations with health indicators.

1.7.2 Use

While the majority of studies focus on neighbourhood exposure to the natural environment, several studies examine the 'use' of natural spaces. This is usually captured as visits to natural places, measured by frequency of visits. The higher the number of visits per week, the greater the feeling that activities in one's life are worthwhile (White *et al.* 2017). Use frequency of bluespaces was associated with self-reported mental and physical health in highly urbanised cities in Germany (Völker *et al.* 2018). Alternatively, dose-response studies have shown that the time spent in natural spaces is important for well-being. For example, longer visits to natural spaces were related to higher levels of recalled restoration in England (White *et al.* 2013c). Visits of 60-119 minutes to blue spaces in Hong Kong were associated with higher levels of recalled wellbeing following a visit than shorter visits (Garrett *et al.* 2019b).

Several studies have studied how the activities carried out while visiting natural places affect the relationship between the natural environment and well-being. In one study in England, activities taken places during visits to natural spaces, such as picnics, playing with children, or exercising were not as restorative as simply walking, and visits to natural spaces were found to be less restorative when visiting with children (White *et al.* 2013c). Activities that involved contact with water were not associated with recalled wellbeing among residents in Hong Kong (Garrett *et al.* 2019b).

Although proximity does not measure 'use' of green- and bluespace, studies have found them to be interlinked. Size, accessibility and distance to urban parks were crucial in explaining use patterns and self-reported well-being in Mexico City (Ayala-Azcárraga *et al.* 2019). For example, visitors to small parks in Mexico City were predominantly from the local neighbourhood, the proportion was less for medium and large parks. Visitors to small parks visited them more frequently but spent less time there than visitors to medium and large parks.

1.8 Analytical approaches and considerations

The majority of studies that examine well-being and the natural environment are cross-sectional in their design (Houlden *et al.* 2018). While providing important contributions to our understanding, this study design suffers from problems relating to confounding and bias and is unable to plausibly infer causality in the associations found. A common dataset used in the UK is the MENE dataset (Monitor of Engagement with the Natural Environment), a repeated cross-section population sample that directly surveys individuals on their use of the natural environment. Other population datasets, such as the national census, that collect data on a number of demographic areas, such as income, education, employment, can be spatially linked to data pertaining to the natural environment using geocoded location data. However, even when repeated cross-section surveys are used, the same issues concerning causality apply, despite reflecting several points in time. Therefore, several recent papers call for more experimental, quasi-experimental and longitudinal studies (Gascon *et al.* 2018; Houlden *et al.* 2018; Kondo *et al.* 2018; Markevych *et al.* 2017).

Experimental studies will normally recruit participants to their study, and the majority involve a walk/activity in locations with differing levels of naturalness (e.g. Coventry *et al.* 2019; Tyrväinen *et al.* 2014). These studies tend to have smaller sample sizes, in large to manage fieldwork cost and time, and it is also difficult to control for all confounding variables. Randomisation methods could account for this problem but this design is rarely used in studies with the natural environment (Kondo *et al.* 2018). Other studies use a quasi-experimental or natural experiment approach, for example in examining the response to nature-based interventions (Hunter *et al.* 2019). Observational studies using longitudinal secondary data, such as cohort samples (e.g., the UK's Millennium Cohort Study) or panel samples (e.g., the UK's Understanding Society programme) contain larger population samples, often collected for a number of reasons, in a multi-partner, multi-funder manner. Cohort samples can be cross-sectional or longitudinal in design, but they differ from panel surveys in that the individuals are sampled with a common shared characteristic, for example all 19,000 participants in the Millennium Cohort Study were born between 2000-2002.

Panel data creates continuous data through time about an individual. Surveys such as the BHPS and the UKHLS allow for analysis at the individual-level, which is different, for example, to repeat cross-sectional surveys which allow for population-level dynamics only to be measured. The construction of the BHPS and UKHLS instruments as prospective annual panels mean data was also collected much more reliably than long-term retrospective history surveys, which suffer from issues such as post-hoc rationalisation and contamination of memory (University of Essex 2016). Panel data can allow quasi-experimental study designs, for example observing how changes in neighbourhood greenspace relate with well-being if respondents move house. This data type also benefits from capturing a wealth of other important data concerning the individual and allows analytical techniques to be employed to reduce problems of bias.

A significant benefit of using longitudinal individual-level panel data is that it allows the use of fixed effects regression. The fixed effects model is useful for causal inference because it controls for all fixed characteristics, both observed and unobserved, that may confound the estimate of the effect of the natural environment on well-being. It allows us to effectively follow the same individuals over time, isolating within-person variation as opposed to between-person variation. This is the equivalent of the repeated measures approach, common in medicine and ecology. This is an improvement on cross-sectional approaches, whose coefficients will be biased by unobserved time-invariant confounders, such as genetics, personality, and experience.

The most important determinant of our confidence that the effect estimate is causal is whether the change in exposure to the natural environment is plausibly unconfounded (Strumpf *et al.* 2017). In this thesis, I include a suite of time-varying explanatory variables in my model specifications to control for heterogeneity in the model. The use of key individual- and neighbourhood-level control variables captures important differences in the economic, social, and environmental conditions that are likely to affect both subjective well-being and the natural environment. The inclusion of these co-variates is led by theory and current understanding in the field (see Dolan *et al.* (2008) for a review of this literature). These commonly observed predictors of an individual's subjective well-being are included in the model development in this thesis, as is common practice across the literature (de Vries *et al.* 2003; White *et al.* 2013b).

Common to all panel surveys are trends in missing data, due to attrition (participants leaving the study), non-response, or by becoming ineligible (e.g. death, moving abroad). Conversely, people can also enter surveys, for example as new temporary sample members moving in and out of the survey (e.g. new cohabiting partners). Respondent attrition is a common problem in panel surveys, and there are consistent coding standards for missing data across UK panel surveys. In this thesis, missing data was imputed in variables where new data could be calculated with a high degree of confidence. Proxy responses were not included in the dataset. Where missing values were caused by non-response, these entries were dropped from the model, except for Age which could be calculated accurately from responses in previous or later waves. In chapter 2, missing data in the Indices of Multiple Deprivation were infilled and extrapolated using trends in the existing years. All missing location and neighbourhood-level data were imputed where possible, for example, LSOA codes were derived in GIS if postcode-level data were available.

The geographic scale of previous studies also varies substantially. Case study sizes have been delimited at country- (de Vries *et al.* 2016; Elliott *et al.* 2018; Mavoa *et al.* 2019b), region- (Annerstedt *et al.* 2012; Cox & Gaston 2016), city- (Houlden *et al.* 2019a; Nath *et al.* 2018; Olsen *et al.* 2019), and site-level (Lindemann-Matthies & Matthies 2018). There are merits to examining the health-nature relationship across at all scales, for example, studies at the city-level are largely able to control for important gradients in urbanicity. Conversely, regional and national studies are able to compare the relationships between urban and rural areas for example, or across different geographical situations such as coasts. Site-level studies effectively control for broader spatial variations in socioeconomic patterns.

This thesis uses England and then London as its case study locations. To observe individual-level well-being data that is also rich in co-variate information, data availability invariably limits the scale at which studies can be conducted. There is a wealth of individual-level data available for the UK, which allowed me to employ statistical methods that were suitable for longitudinal well-being data. However, several explanatory variables were only available for England, which then limited the extent of the study. The same is true for data relating to the natural environment, which generally improves in quality and resolution the smaller the spatial scale. This explains why my later chapters focus on one city, London. This allowed me to access large, detailed open space and biodiversity datasets that are not available consistently at larger scales.

Another consideration is the sample population used. I use two different population samples across this thesis, the BHPS and the UKHLS. Despite both the BHPS and UKHLS being representative samples of the UK population, they have underlying differences in their sampling structure, and therefore spatial distribution, and their demographic composition and representativeness. To focus the research question and to use the longest possible time series of individuals, in one chapter I only use the BHPS (chapter 4). In two chapters (chapters 3 and 5) I use both the BHPS and UKHLS separately, which enables me to compare the possible differential relationships between characteristics of these population samples and the natural environment. In chapter 2, I take a different approach and combine the two datasets to create a longer time series corresponding to the air pollution data time series. The different approaches across the thesis enable me to answer additional questions about the relationship between individual well-being and the natural environment and make unique contributions to understanding.

Another consideration when employing different analytical techniques is the statistical operationalisation of well-being metrics. Common subjective well-being measures, such as life satisfaction, are treated as either ordinal or cardinal in nature, and this then determines the statistical method used (e.g. ordinary least squares regression or ordered logit models). Most well-being data are on ordinal scales (Brown 2015), meaning they are ordered by nature and each class is therefore greater than the previous. However, most studies use life satisfaction environmental valuation approaches assume cardinality in the dependent well-being variable. Reassuringly, studies that use both ordinal and cardinal structure find little difference in their empirical findings (Brereton *et al.* 2008; Ferrer-i-Carbonell & Frijters 2004; Levinson 2012; Mackerron & Mourato 2008).

It is also clear from the current literature that the relationship with the natural environment differentiates with subjective well-being measures. Studies that use several measures of well-being report different outcomes across the measures (Houlden *et al.* 2018; Jarvis *et al.* 2020b; White *et al.* 2013a), and different outcomes across different exposure methods (Cox *et al.* 2018; White *et al.* 2017). More research studies involving multiple measures of well-being are needed to better understand how different facets of well-being relate to the natural environment.

To address this research gap, in this thesis I use a variety of well-being measures as independent variables. In each chapter, the well-being measures selected are based upon current understanding and theory-driven model-building. Life satisfaction is used in every chapter as it is the most common and consistently used subjective well-being measure globally. Mental health is included in all chapters relating to characteristics and quality of green- and bluespaces, as previous research has shown that exposure to these natural spaces could have considerable mental health benefits. As a third measure, self-reported general health is included in the two chapters that examine the broadest range of open space categories and characteristics.

1.9 Thesis rationale and aims

1.9.1 Aims

The main aims of this thesis are (1) to identify which characteristics and qualities of the natural environment are important for subjective well-being, (2) to examine if the *quality* of the natural environment affects subjective well-being, and if so, to estimate the effect size, (3) to consider different ways of measuring proximity or exposure to the natural environment.

In this thesis, I have explored some of the key evidence gaps in the natural environment and human well-being literature. Primarily, I have addressed the issues of capturing characteristics and quality metrics of the natural environment and exploring the effect with well-being. I identified air pollution, specifically nitrogen dioxide (NO_2), land use and habitat type, site designation, and biodiversity as measures of characteristics of the natural environment. I considered the effect of having access to private open space on the relationship between well-being and public open space. I addressed issues regarding the measurement of access or exposure to the natural environment by using a variety of different approaches, such as neighbourhood proportion, network analysis and distance decay. I used longitudinal individual-level data from the British Household Panel Survey and the UK Household Panel Study, and up to three well-being measures to examine the multi-dimensional nature of well-being. I also included a suite of important explanatory variables to reduce the effect of bias in my models.

1.9.2 Study region

In this thesis, I use England, and then Greater London as my study areas. In England, at mid-year 2014, 45.0 million people, or 83.0% of the population, lived in urban areas, with 9.3 million (17.0%) living in rural areas (Defra 2018). This concentration of the English population living in urban areas highlights the need to understand what drives subjective well-being in them (Hand 2020). In September 2018, average life satisfaction in UK adults was 7.69/10. In 2012/13 77% adults aged 16 or over in the UK rated their life satisfaction at 7 or more out of 10. In 2013/14, 27% adults aged 16 or over in the UK rated their life satisfaction at 9 or 10 out of 10. However, 6% rated it as 4 or lower out of 10. That's approximately 4 million people with very low subjective well-being.

In 2016, The Mental Health Foundation reported that each week 17.6% of adults in England (approximately 1 in 6) report symptoms of at least one common mental disorder, such as anxiety or depression (Mental Health Foundation 2016). The report also states that over a third (34%) of people with mental health problems rate their quality of life as poor, compared with three per cent of those without mental illness. The 2013 Chief Medical Officer's report estimated that the wider costs of mental health problems to the UK economy are £70–100 billion per year – 4.5% of GDP (Department of Health 2014). However estimating this economic cost is difficult, with another analysis estimating the cost of mental health in the UK at over £94 billion a year, approximately 4% of GDP (OECD 2018).

The UK's Office for National Statistics (ONS) began the Measuring National Well-Being programme in 2010 to assess UK well-being levels across 10 domains (e.g. health, income, where we live and the natural environment). In May 2013, the most influential factors affecting personal well-being were self-reported health, employment status and relationship status, underpinned by the sense of choice and contentment with their situation (ONS 2013). However, there is now a growing recognition in government that clean air and green- and bluespaces are critical assets for delivering health and well-being benefits to individuals (Public Health England 2020). For example, Natural England, (2009) estimate that £2.1 billion would be saved annually through averted health costs if everyone in England had equal good perceived and/or actual access to green space, and more recently Fields in Trust (2018) estimated that publicly accessible parks and greenspaces across the UK provide people with over £34 billion of health and wellbeing benefits. In 2017, the health and social care costs of $PM_{2.5}$ and NO_2 air pollution in England reached £157 million, and they are predicted to reach £18.6 billion by 2035 unless action is taken (Public Health England 2018). Moreover, it is estimated that 2.69 million people in GB do not live within a 10 minute walk of a greenspace (Fields in Trust 2018), and 13% of UK households do not have access to a private garden (Gibbons *et al.* 2014).

In the UK, levels of NO_2 regularly exceed legally enforced EU air quality standards, such as those set out in the EU Ambient Air Quality Directive and the fourth Daughter Directive. Air quality management is largely driven by European (EU) legislation which England has passed as law, as part of The Air Quality Standards Regulation 2010. These directives (e.g. EU directives 2008/50/EC, 1996/62/EC, and 1999/30/EC) set out legal daily exceedance and annual mean levels of several ambient outdoor air pollutants, including NO_2, to protect and improve human well-being (European Commission 2019). The legal NO_2 annual mean 40 $\mu g/m^3$ is exceeded in parts of the UK every year.

These issues are perhaps even more prominent in the capital, London. Greater London is a large and densely populated city; London's land area represents only 0.65% of the UK's total land area but is home to 13.36% of the UK's total population. London experiences some of the lowest air quality levels in the country. In January 2017, $PM_{2.5}$ levels in London were worse than in Beijing, China, a city that is notorious for poor air quality (Hswen *et al.* 2019), and each year air pollution from outdoor sources contributes to nearly 9500 early deaths in London, a quarter of the national total (Hswen *et al.* 2019). Londoners have just 18.96 m^2 of greenspace provision per person, which is almost half the national average (Fields in Trust 2020). Recent research revealed that 1 in 5 Londoners do not have access to a private garden, which is higher than the national average at 1 in 8 for British households (Office for National Statistics 2020b). Despite this, Londoners enjoy greater *access* to public greenspace than the national average; 44% of Londoners living within a five-minute walk of a park, compared to 28% of people across Britain (Office for National Statistics 2020b). London's parks and open spaces are estimated to save the city £950 million in health care costs (Mayor of London 2020).

London is ranked tenth across 30 global cities, by public greenspace percentage area per capita (World Cities Culture Forum 2017). It is approximately comparable to Rome, Madrid and Rio de Janeiro, and above New York and Berlin. In July 2019, London became the world's first National Park City. This makes it a particularly interesting urban area to study as it has a current agenda to improve the quality and use of its natural environments. London supports a wide diversity of wildlife habitats, with over 13,000 species recorded over the last 50 years (London Wildlife Trust 2015). These habitats are threatened with loss or damage by development pressures and without protection and management, the overall quality of London's natural environment is likely to be damaged over time (London Wildlife Trust

2015). London's biodiversity is following the same declining trajectory as that in England and the UK overall. Public sector expenditure on biodiversity in the UK, as a proportion of GDP, has fallen by 42%, following a peak in 2008/9 (State of Nature Partnership 2019). In England, more species are experiencing population decreases than increases, and 13% of species in England are threatened with extinction (State of Nature Partnership 2019). Uncovering the potential importance of biodiversity on supporting human health and well-being is likely to improve the support for, and protection of, biodiversity in London.

Additionally, the recent global pandemic due to the Covid-19 outbreak has highlighted the importance of the natural environment for individuals. In a recent public opinion poll, 87% of respondents agreed that living close(r) to spaces that are rich in wildlife and nature is/would be an advantage during the Coronavirus (COVID-19) outbreak, and 77% agreed that visiting nature has been important for their general health and happiness during the outbreak (RSPB 2020). In the same poll, 89% of respondents agreed increasing the amount of accessible nature-rich green space will help to improve people's general health, well-being and happiness. Only 5% disagreed.

There is a clear need and interest in the UK to better understand the determinants of well-being, and particularly seeking opportunities to improve the well-being of urban populations should be a priority (Taylor *et al.* 2018). There are also key evidence gaps in understanding of the relationship between the natural environment and individual well-being measures. In a recent Defra evidence statement, it was highlighted that there is mixed or unclear evidence for the well-being benefits of the type of natural environment, environmental quality and biodiversity, as well as suitable exposure modes (Defra 2017). They suggest more research to use longitudinal and robust methods, as well as exploring methods and recommendations for policy implementation.

1.9.3 Thesis structure

Chapter 2: Examining the effect of nitrogen dioxide (NO_2) on life satisfaction

This chapter explores the relationship between air pollution and subjective well-being in England. In order to estimate the welfare effects of exposure to nitrogen dioxide (NO_2), I combine subjective well-being data from the British Household Panel Survey (BHPS) and UK Household Longitudinal Study (UKHLS) with detailed air quality records held by the UK Department for Environment, Food and Rural Affairs (DEFRA). To address endogeneity concerns, I linked these with a variety of geo-referenced datasets capturing differences in economic, social and environmental conditions across neighbourhoods. I also took advantage of the panel nature of our data by employing individual fixed effects and used road traffic counts and road density as instruments for NO_2. My results suggest a significant and negative association between mean annual ambient NO_2 and life satisfaction, and moreover that these effects are substantive and comparable to that of many 'big hitting' life events such as unemployment, marital separation and widowhood.

Chapter 3: One size does not fit all: how type of urban open space matters when exploring the link with well-being

In this chapter, I examined the relationship between different land use types and subjective well-being in Greater London, UK. I used the Planning Policy Guidance Note 17 (PPG17): *Planning for open space, sports and recreation* to categorise open spaces, and calculated neighbourhood proportion of each category and subcategory. Three subjective well-being measures were used (life satisfaction, mental health and self-reported general health) from adults in the BHPS and UKHLS surveys, and fixed effects regression was employed to explore the relationship with land use types. My findings suggest positive and negative relationships found with different land uses, and that bluespaces should be identified separately from greenspaces. I also highlight that the localised context of land uses, such as the likely beneficiaries and the specific mechanisms that deliver these (dis)benefits, must be considered in future work.

Chapter 4: The association between the quality of public green and blue spaces and subjective well-being in London

In chapter 4, I examined the impact of the quality of public natural spaces on subjective well-being, where quality is defined as its importance for nature conservation. I also explored the impact of private open spaces on well-being, and if this affected the relationship between public open spaces and well-being. I used two Greenspace Information for Greater London (GiGL) areas of deficiency datasets; deficiency to Sites of Importance for Nature Conservation (SINCs) and deficiency to Public Open Spaces (POSs). SINCs are open spaces that have significant biodiversity importance, and we use biodiversity as a proxy for quality. Deficiency was calculated as living more than a 1km walk from a POS or SINC (calculated using actual travelling routes and known access points). I used all adults in the BHPS, two measures of subjective well-being (life satisfaction and GHQ), and a suite of spatially explicit explanatory variables. I found that the *quality* of public green and blue spaces is important for the well-being of residents in London. These results also suggest that access to private open space has a positive and significant relationship with well-being, which is separate to that with public open space. Therefore, both public and private green and blue spaces are important for well-being for residents in London.

Chapter 5: Does wildlife make us happy? Investigating the relationship between biodiversity and subjective well-being

In chapter 5, I examined the relationship between habitat and biodiversity and subjective well-being in adults in Greater London, UK. I used detailed habitat, species presence databases and Normalised Difference Vegetation Index (NDVI) layers to calculate environment metrics. I used two different methods for capturing exposure: neighbourhood composition and distance-decay functions to open space sites (OSS). I then used these exposure scores to conduct fixed effects regression, using three measures of subjective well-being from the BHPS and the UKHLS to explore the multi-dimensional nature of well-being (life satisfaction, mental distress (GHQ) and self-reported general health). Results suggest that habitat diversity is not important for well-being, but certain habitat types are, and that biodiversity might be important for well-being. These relationships differ between population sample, well-being measure and exposure methods used. Our findings are important for policy-makers and conservation organisations who seek to better understand the link between biodiversity and human health and well-being, in order to better promote both.

Chapter 6: General Discussion

This final chapter summarises the key findings from my thesis and provide an overarching discussion based on my thesis aims. Here I provided my conclusions and suggest potential future research ideas.

Chapter 2: Examining the effect of nitrogen dioxide (NO_2) on life satisfaction

2.1 Abstract

In order to estimate the welfare effects of exposure to nitrogen dioxide (NO_2), we combine subjective well-being data from the British Household Panel Survey (BHPS) and UK Household Longitudinal Survey (UKHLS) with detailed air quality records held by the UK Department for Environment, Food and Rural Affairs (DEFRA). To address endogeneity concerns, we linked these with a variety of geo-referenced datasets capturing differences in economic, social and environmental conditions across neighbourhoods. We also took advantage of the panel nature of our data by employing individual fixed effects and used road traffic counts and road density as instruments for NO_2. Our results suggest a significant and negative association between mean annual ambient NO_2 and life satisfaction, and moreover that these effects are substantive and comparable to that of many 'big hitting' life events such as unemployment, marital separation and widowhood.

2.2 Introduction

Local environmental amenities such as clean air play a significant role in our quality of life. Much previous research, for instance, has highlighted the importance of proximity/exposure to green space (Pretty *et al.* 2005; Takayama *et al.* 2014) and blue space (Bell *et al.* 2015a), climate (Feddersen *et al.* 2016), biodiversity (Dallimer *et al.* 2012; Fuller *et al.* 2007) and air quality (Ambrey *et al.* 2014; Luechinger 2009; Welsch 2006) for our overall well-being. But how much value do we put on environmental features relative to other factors that affect our utility? Unfortunately, environmental amenities often do not have prices and will therefore be typically underprovided by the market. However in order to provide a clear rationale for environmental management and regulation, it is important to calculate how much value people attribute to environmental features (Srinivasan & Stewart 2004; Welsch & Kühling 2009).

Typically economists have relied on stated and revealed preference methods to estimate the utility gains/losses associated with changes in the provision of environmental goods and services (Egan *et al.* 2015; Kuminoff *et al.* 2010). Stated preference studies construct a hypothetical contingent market where the individual is asked to state their willingness to pay for the non-market good in question, whereas revealed preference methods such as Hedonic Pricing try to infer the value of non-market goods by observing the actual behavior of individuals, e.g. their choice of home (Chay & Greenstone 2005; Kim *et al.* 2003).

Both methods have their advantages and disadvantages. Revealed preference methods, for instance, reflect real-life decisions that are conducted in actual markets and so avoid the hypothetical bias associated with stated preference methods. One disadvantage with this approach is that consumer decisions are based on perceived rather than objective perceptions of environmental features. If adequate information on the provision of environmental features (e.g. level of air pollution or amount of open space) is missing or at least not readily apparent, an individual's subjective assessment may not correspond with the objective measures. This could lead to biased estimates of an individual's willingness to pay for environmental amenities (Frey *et al.* 2010; Luechinger & Raschky 2009).

Stated preference methods such as contingent valuation are extremely flexible in that they allow valuation of a wider variety of non-market goods and services than is possible with revealed preferences. A limitation with this methodology is that it is susceptible to hypothetical bias and framing problems (Lusk & Norwood 2009; Murphy *et al.* 2005). More specifically, individuals may find it difficult to provide realistic value estimates due to difficulty evaluating hypothetical choice tasks.

As an alternative to these methods, the use of subjective well-being data has been increasingly used as a mechanism for communicating the welfare effects stemming from exposure to environmental (dis)amenities. With this approach, subjective well-being is used as a proxy for individual utility and indicators of environmental quality are entered as an explanatory variable in a micro-econometric life satisfaction equation. It has been used, for example, to derive a value or, put differently, to illustrate the 'psychological' cost associated with ecosystem diversity (Ambrey & Fleming 2014), airport noise (van Praag & Baarsma 2005), flood disasters (Luechinger & Raschky 2009), climate (Maddison & Rehdanz 2011), scenic amenity (Ambrey & Fleming 2011), green space (Krekel *et al.* 2016; Tsurumi & Managi 2015) and air quality (Ambrey *et al.* 2014; Ferreira *et al.* 2013; Levinson 2012; Luechinger 2009; Mackerron & Mourato 2008; Orru *et al.* 2016; Zhang *et al.* 2017a).

In this paper, we use subjective well-being data as a means to estimate the welfare losses associated with exposure to nitrogen dioxide (NO_2). We concentrate on NO_2 in this paper as it is a significant gaseous pollutant across the UK, emitted from road traffic and energy production processes. It is a precursor to particulate pollution and low-level ozone and as such highly relevant for human well-being (Brook *et al.* 2010; Brunekreef *et al.* 2015; Shah *et al.* 2015). In addition, levels of NO_2 regularly exceed legally enforced EU air quality standards, such as those set out in the EU Ambient Air Quality Directive and the fourth Daughter Directive. Air quality management is largely driven by European (EU) legislation which England has passed as law, as part of The Air Quality Standards Regulation 2010. These directives (e.g. EU directives 2008/50/EC, 1996/62/EC, and 1999/30/EC) set out legal daily exceedance and annual mean levels of several ambient outdoor air pollutants, including NO_2, to protect and improve human well-being (European Commission 2019). The legal NO_2 annual mean 40 μg/m^3 is exceeded in parts of the UK every year. Higher levels of NO_2 emissions are largely attributable to increasing numbers of diesel vehicles on the roads. By 2013, diesel cars made up 34.5% of the licensed car total in Great Britain, up from 7.4% in 1994 (Department for Transport, 2014). Therefore, the study of NO_2 exposure on human well-being also has significant implications for transport policy in the UK.

While there has been little previous work examining the role of NO_2 on life satisfaction, there is a growing body of literature which have estimated the relationship between other indicators of air quality, such as particulate matter (PM_{10}) and sulphur dioxide (SO_2) with well-being. For example, Ambrey et al., (2014) and Ferreira and Moro (2010) using cross-sectional data find a negative association with PM_{10} and subjective well-being in Australia and Ireland respectively. Levinson (2012) also finds a negative association between PM_{10} and well-being in the United States by using an innovative approach where he was able to match happiness data with air pollution data on the day and place individuals were surveyed. Looking at SO_2, Ferreira et al., (2013) conduct a cross-sectional analysis of the European Social Survey and find a negative association between SO_2 and life satisfaction. Luechinger (2009) uses longitudinal panel data and high spatial resolution air pollution data to explore the relationship between SO_2 and life satisfaction in Germany. He uses respondents' locations upwind and downwind of large power plants that installed emissions control equipment as an instrument for SO_2 emissions and similarly to Ferreira et al., (2013) observes a significant negative association between SO_2 and life satisfaction.

We are aware of three prior studies that have examined the relationship between NO_2 and subjective well-being (Du *et al.* 2018; Mackerron & Mourato 2008; Welsch 2002, 2007). The analysis by Mackerron and Mourato (2008) relies on a cross-sectional analysis of approximately 400 Londoners and finds a 10 $\mu g/m^3$ increase in NO_2 is associated with an average decrease of 0.5 across an 11 point scale of life satisfaction. Du et al., (2018) use a similar cross-sectional approach in a comparative city analysis in China. They report a 10 $\mu g/m^3$ increase in NO_2 is associated with a decrease of 0.06 and 0.05 across an 11 point scale of life satisfaction in Beijing and Shanghai respectively. Welsch (2002, 2007) considers the relationship between NO_2 and average self-reported happiness using cross-sectional data for 54 countries and finds a 1 kiloton increase in urban NO_2 is associated with a 0.003 decrease in average population happiness across a 4-point scale.

While these studies have made an important contribution to the subjective well-being literature, their estimates are potentially affected by various sources of endogeneity bias. For instance, Welsch relies on relatively large geographical units of analysis (e.g. country-level) as well as uses average reported well-being across countries as opposed to well-being reported at the individual level Second, all of these studies are at risk of confounding the effects of air quality with the effects of unobserved factors, such as differences in economic, social and environmental conditions across neighbourhoods which may be related to both air pollution and individuals' subjective well-being.

To the best of our knowledge, this study is the first analysis of the relationship between NO_2 and subjective well-being that takes account of these endogeneity issues. First, to help isolate the effect of NO_2 from other confounding variables, we link our survey and environmental datasets recording individual's well-being and exposure to NO_2 with a variety of external geo-referenced datasets capturing differences in economic, social, and environmental conditions across neighbourhoods. The datasets include the English Indices of Deprivation available from the Department for Communities and Local Government (DCLG) which record relative levels of deprivation in 32,482 small areas or neighbourhoods, called Lower-layer Super Output Areas (LSOA) in England, and estimates of population density available from the Office for National Statistics (ONS). Second, we use estimates of green and blue space available from the Generalised Land Use Database (GLUD), available from DCLG also at the LSOA level. To account for other sources of unobserved time-invariant heterogeneity (e.g. personality traits), we take advantage of the panel nature of our dataset by adopting a fixed effects regression approach. Finally, as a robustness check we instrument NO_2 with annual average daily traffic flow (AADF) counts and road density. Traffic flow and road density are significantly related with NO_2 levels, but we argue exogenous to subjective well-being after conditioning on a wide set of control varibables such as economic and social deprivation, population density and commuting patterns.

We find that NO_2 is significantly related with subjective well-being, albeit much smaller in magnitude than previous estimates after controlling for a variety of important spatial controls. That being said, the effect size is substantive and comparable to that of many other widely studied determinants of subjective well-being such as unemployment status, marital separation and widowhood. Given that the effect of NO_2 is, to some extent, experienced by everyone (i.e. not everyone is unemployed but everyone is subject to a certain level of NO_2 exposure) this suggests that the welfare gains to society from reductions in exposure to NO_2 can be substantive. Furthermore, our results highlight significant geographic inequalities in the disutility impacts of $NO_{2.}$ For example, the average disutility impacts associated with NO_2 from living in parts of the South West of England as opposed to central London would exceed the disutility associated with many other significant life events such as marital separation and widowhood.

2.2.1 Subjective measures of well-being

One of the central assumptions underpinning neo-classical economics is that utility is formed based on the consumption of goods, and that individuals will always make decisions that maximise their individual utility. There is much research to suggest, however, that individuals may make sub-optimal decisions due to cognitive biases and inadequate information (McFadden 1999; Rieskamp *et al.* 2006; Sen 1977). In other words, behaviour may not always be reflective of rational self-interest. This has led to an emerging body of research seeking to base assessments of welfare on experience utility (i.e. happiness data) rather than choice based methods such as revealed preferences (Clark *et al.* 2008; Krueger & Schkade 2008). Proponents behind the use of experience utility as a welfare criterion for public policy seek to explore what factors affect people's subjective well-being and use such information to inform economic and social policy (e.g. Donovan and Halpern, 2002; Kahneman and Sugden, 2005; Layard, 2005; Treasury, 2008; Dolan and Metcalfe, 2012; OECD, 2013). This approach also recognises that while consumers are becoming increasingly satiated with products, this is often not matched by increases in how they rate their quality of life (Forgeard *et al.* 2011; Hirschauer *et al.* 2015).

Emerging interdisciplinary research has begun to address concerns regarding the reliability of using subjective measures of well-being as an approximation for individually experienced welfare or utility. They have been shown to have a high scientific standard in terms of internal consistency, reliability and validity (Frey *et al.* 2010) and have been shown to be stable over time (Diener *et al.* 1999). They have been found to be consistent with third party respondent evaluations, for example, with those who report high satisfaction with their life also reported as being satisfied by family members, friends and experts (Sandvik *et al.* 1993). Subjective well-being measures have also been shown to be directly associated with physical reactions that can be thought of as describing true internal happiness. For example visible signs of cheerfulness such as smiling have been positively associated with self-reported happiness (Di Tella & Macculloch 2006). Happier nations tend to have lower levels of hypertension (Blanchflower & Oswald 2008) and lower suicide rates (Di Tella *et al.* 2003), and low levels of subjective well-being have been associated with reported chronic pain and unemployment (Kahneman & Krueger 2006).

When we use subjective measures of well-being (e.g. self-reported life satisfaction) as a valid approximation for individually experienced welfare or utility, we can calculate the welfare effects of environmental goods by estimating a micro-econometric life satisfaction function with the environmental variable(s) of interest (e.g. NO_2) included as an explanatory variable. The coefficients from this equation can then be used to estimate the 'psychological' cost of exposure to an environmental disamenity such as NO_2, relative to other factors that are related with subjective well-being. While not without its own limitations, this approach avoids some of the difficulties inherent with stated and revealed preferences. For example, it is less likely to suffer from hypothetical bias and framing problems associated with stated preference techniques. It is also less cognitively demanding for respondents and there is no reason to expect answers to be affected by strategic behaviour. In fact, people may not even be aware that there is a cause-effect relationship between environmental conditions and their self-reported life satisfaction (Frey *et al.* 2010). Furthermore, in contrast to revealed preference methods, it neither presumes rational agents nor does it need to rely on assumed equilibrium in private market transactions to estimate the value of public goods (Ferreira & Moro 2010; Neuteleers & Engelen 2015).

2.3 Methods

2.3.1 Sample

The British Household Panel Survey (BHPS) and the UK Household Longitudinal Survey (UKHLS) are large multi-year panel surveys collecting individual and household information from a representative UK sample population and are part of the Understanding Society project (University of Essex. Institute for Social and Economic Research. NatCen Social Research. Kantar Public 2016; University of Essex. Institute for Social and Economic Research 2014). Demographic, socio-economic, health and geographic data are collected in both datasets, as well as that pertaining to attitudes, opinions and values. The BHPS runs from 1991 to 2008 (waves 1-18) and collected information from over 10,000 individuals (5000 households). The UKHLS runs from 2009 to present day, with data currently available to 2014 (waves 1-5), collecting information from over 50,000 individuals (40,000 households). Data collection for each wave in the BHPS is undertaken within a single year but the UKHLS uses an overlapping panel design with data collection for a single wave conducted across 24 months. Interviews are typically carried out face-to-face in respondents' homes by trained interviewers. BHPS participants continue to be interviewed as part of the UKHLS and are present from wave 2 onwards. The two datasets were combined to create a longer time series. Waves 1-5 of the UKHLS are taken as waves 19-23 of the BHPS, creating a continuous time series. As BHPS waves are collected each calendar year and UKHLS waves over two years, both wave and interview year variables are maintained.

The measure of subjective well-being used in this study is based on respondents' answer to the following question: 'How dissatisfied or satisfied are you with life overall?' Respondents give a single reply from a Likert scale with options ranging from 7 ('completed satisfied') to 1 ('completely unsatisfied'). Life satisfaction is one of the most commonly used subjective well-being measures in the literature to date. Fortunately, this subjective well-being question is consistent across both surveys but was not asked in the BHPS wave 11 (relating to the year 2001) so we restricted the analysis to begin in 2002. Based on prior literature, we include a rich set of commonly observed predictors of an individual's subjective well-being in our regression analysis (see Dolan et al., (2008) for a review of this literature). These include socio-economic factors such as income, age, gender, relationship status, health, education, and labour force status (see Table 2.1 for a more detailed explanation of all the variables used in the analysis). A year variable was included to account for any natural temporal progression in the data.

Table 2.1. Descriptive statistics of variables included in analysis.

Variable name		Mean or %	St. dev.	N
Life satisfaction	Respondent’s self-reported life satisfaction (scale 1 to 7)	M=5.154	1.437	203426
NO_2	Mean annual ambient nitrogen dioxide (NO_2) in respondent’s residential LSOA (μg/m^3)	M=19.668	7.641	244389
Annual household income	Log equivalent annual household income (income divided by square root of household size)	M=7.433	0.725	241299
Age	Respondent’s age in years	M=46.279	18.460	244389
Age-squared	Respondent’s squared-age in years	M=2482.53	1833.16	244389
Female	Respondent is female (yes/no)	53.38%	0.499	244389
University-level qualification	Respondent has a university-level qualification (yes/no)	29.63%	0.457	244389
Marital status				
Single and never married	Respondent is single and has never been married/civil partnership (yes/no)	22.47%	0.417	244205
Married	Respondent is married (yes/no)	51.87%	0.500	244205
Separated	Respondent is separated but still married/civil partnership (yes/no)	1.71%	0.130	244205
Widowed	Respondent is widowed (yes/no)	5.79%	0.233	244205
Divorced	Respondent is divorced/dissolved civil partnership (yes/no)	6.07%	0.239	244205
Living as couple	Respondent is living as a couple (yes/no)	12.04%	0.325	244205
Employment status				
Employed	Respondent is employed (yes/no)	48.24%	0.500	244389
Self-employed	Respondent is self-employed (yes/no)	7.60%	0.265	244389
Unemployed	Respondent is unemployed (yes/no)	5.07%	0.216	244389
Retired	Respondent is retired (yes/no)	20.98%	0.407	244389
Caring for family	Respondent is caring for family (yes/no)	6.97%	0.255	244389
In training	Respondent is in training (yes/no)	7.09%	0.257	244389
Disabled	Respondent is disabled (yes/no)	3.40%	0.181	244389
Other	Respondent is categorized as other (yes/no)	0.18%	0.042	244389
Health satisfaction				

Variable name		Mean or %	St. dev.	N
Completely or very satisfied with health	Respondent is completely or very satisfied with their health (yes/no)	47.15%	0.499	203797
Less than very satisfied with health	Respondent is less than very satisfied with their health (yes/no)	52.85%	0.499	203797
Commuting time				
Non-commuters	Respondent does not commute (yes/no)	49.22%	0.500	224170
1-15 minutes	Respondent has a commute between 1-15 minutes (yes/no)	21.75%	0.413	224170
16-30 minutes	Respondent has a commute between 16-30 minutes (yes/no)	15.93%	0.366	224170
31-50 minutes	Respondent has a commute between 31-50 minutes (yes/no)	7.12%	0.257	224170
>50 minutes	Respondent has a commute of over 50 minutes (yes/no)	5.98%	0.237	224170
Time variables				
Year	Year of interview			244389
Wave	BHPS or UKHLS wave			244389
Spatial control variables				
Population density	Population of residents per km^2 in respondent's residential LSOA	M=4225.008	4345.957	244389
Crime deprivation	Indices of Multiple Deprivation – risk of personal and material victimisation in the LSOA	M=0.017	1.042	244389
Income deprivation	Indices of Multiple Deprivation – proportion of the population experiencing deprivation relating to low income in the LSOA	M=0.142	0.108	244389
Geographical deprivation	Indices of Multiple Deprivation – proportion of the population experiencing deprivation relating to isolation from key local services	M=37.516	42.962	244389
Area of greenspace	Percentage of LSOA designated as greenspace and/or domestic gardens	M=67.310	20.176	244389
Area of water	Percentage of LSOA designated as surface water	M=1.635	5.886	244389

Each individual in the BHPS and UKHLS datasets has a geographic identifier at the LSOA level (32,482 LSOAs in England) for each wave. This geographic identifier allows us to link each individual in the household survey with a number of neighbourhood level datasets, including those recording NO_2 levels. LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). As other neighbourhood-level control variables are only available for England we limit our analysis to this extent. The mean area of an English LSOA is 4km^2. Due to population fluctuations approximately 5% of LSOAs changed in 2011 (split, merged or deleted). We use the 2001 LSOA structure and, for consistency across time, any individual who has lived in the LSOAs that changed were removed from this study.

2.3.2 Air pollution

Ambient outdoor NO_2 data were obtained from the UK's Department for Environment, Food and Rural Affairs (Defra) as pollution-climate modelled values (Defra 2016). These datasets allow the UK Government to report air quality levels to EU Air Quality Directives and allow for us to examine the effects of relatively localised air quality changes. These are outputs based on dispersion modelling using point sources of known emission levels (e.g. monitoring stations, power stations, roadsides) and UK meteorological data, and are available as 1km x 1km grids for the UK as the annual mean NO_2 in µg/m^3. For each year within 2002-2014, each LSOA was given the pollution value of the nearest NO_2 point to each LSOA population-weighted centroid. This was calculated using the Spatial Join tool in ESRI ArcGIS v10.3.1 (ESRI 2015). The pollution values were then attributed to every individual residing in each LSOA using the corresponding LSOA and year variables in Stata 12 (StataCorp 2011).

In Figure 2.1 we provide a visual illustration of the geographical variation in annual ambient outdoor NO_2 levels across England. The mean value for England in 2014 was 9.95 µg/m^3 and a standard deviation of $\pm$5.03. The overall mean for all years 2002-2014 was 11.6 µg/m^3. As expected, the maximum annual ambient level of NO_2 recorded in 2014 occurred in central London (57.68 µg/m^3) and the minimum in Cornwall and Devon (2.83 µg/m^3). In 2014, the locations which exceeded the legal annual ambient level of 40 µg/m^3 were in London, London Heathrow airport, Birmingham, Sheffield, and Southampton. This is likely due to relatively high levels of traffic volume and density in these areas.

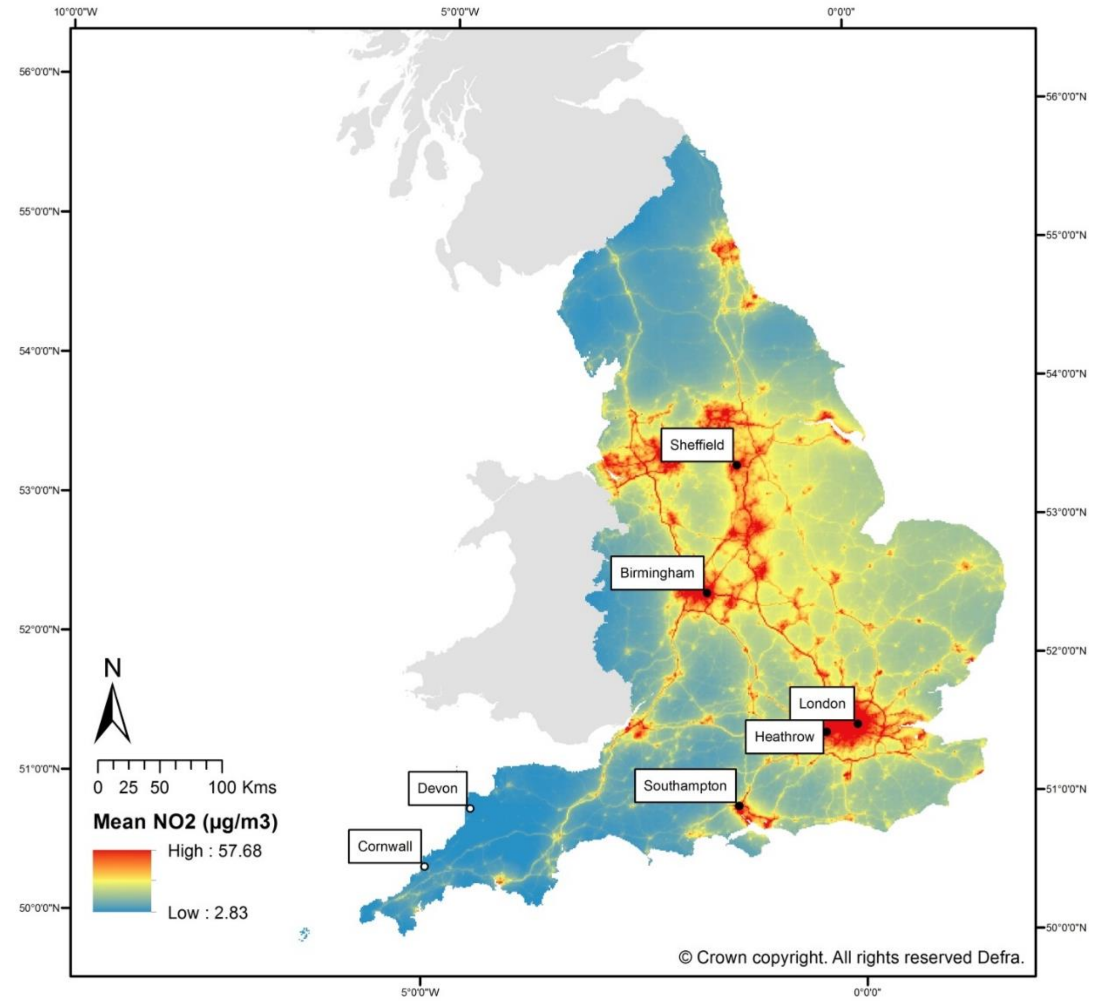

Figure 2.1. Mean ambient outdoor NO_2 levels in 2014.

2.3.3 Spatial control variables

To obtain measures of deprivation in the respondents' neighbourhood we linked our household survey data (BHPS and UKHLS) with the English Indices of Multiple Deprivation. These are calculated every 2-5 years by the Department for Communities and Local Government (DCLG) and are based on 37 separate indicators, organised across seven distinct domains of deprivation (Department for Communities and Local Government 2004, 2007, 2010, 2015). Using this data, we are able to match each respondent in our survey datasets with a number of variables reflecting the prevailing economic and social conditions in their neighbourhood. In this analysis we include the Income Deprivation domain and the Geographical Barriers sub-domain (from the Living Environment Deprivation domain) which measure the proportion of the population experiencing deprivation relating to low income and isolation from key local services such as GP surgeries and supermarkets respectively. We also include the Crime Deprivation domain which reflects the risk of personal and material victimisation. The data for 2004, 2007 and 2010 were obtained and linearly interpolated/extrapolated to create an annual time series. These domains were selected due to their theoretical significance on life satisfaction.

Population density measures were calculated for each year using the annual LSOA mid-year population estimate figures obtained from the Office for National Statistics (Office for National Statistics 2016). These data are calculated from census, natural change and migration figures for each LSOA, and are useful to account for any urbanity effects on life satisfaction. We also added in additional control variables capturing differences in green and blue space across LSOAs as these have been shown to be significantly related with life satisfaction and are also likely to be significantly correlated with NO_2 (Jeanjean *et al.* 2016; McDonald *et al.* 2007; White *et al.* 2013b). We calculated measures of green and blue space using data from the Generalised Land Use Database 2005 (GLUD; Department for Communities and Local Government 2005). The GLUD is a dataset providing statistics for nine land use categories for each English LSOA. The dataset is based upon the Ordnance Survey MasterMap January 2005 and is accurate to a spatial resolution of 10 m^2. The proportion of land categorised as green space or domestic garden (we combined these as per White et al., (2013)), and surface water, within each LSOA area were used as measures of natural land use.

2.3.4 Estimation approach

The micro-econometric life satisfaction equation was constructed as follows:

$$LS_{ijt} = \beta_0 + \beta_1 N_{jt} + \beta_2 L_{jt} + \beta_3 X_{it} + \beta_4 T_t + \varepsilon_{ijt}$$

Where LS is the dependent variable, life satisfaction, for an individual i, at a given location j and in a given year t. It is a function of the annual ambient outdoor mean value of NO_2 (N_{jt}), a vector of LSOA neighbourhood factors (L_{jt}) and individuals' socio-economic and demographic characteristics (X_{it}), and a year variable (T_t). ε_{ijt} is the error term (all remaining unaccounted for variation). All spatial analysis was carried out in ArcGIS v10.3.1 and regression analysis using the regress and xt suites in Stata 12 software. We first used a pooled cross-sectional approach to estimate the above equation (clustered by LSOA to obtain robust standard errors) and then took advantage of the panel nature of the data by using fixed effects. Fixed effects have a significant advantage over cross-sectional correlations as we will be effectively following the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits) that could be related with both NO_2 and life satisfaction.

2.4 Results

2.4.1 Main results

Our main results are summarised in Table 2.2. In our baseline pooled cross-sectional model which includes NO_2 as well as socio-demographic controls (specification 1 in Table 2.2) we find that NO_2 is significantly and negatively related to life satisfaction ($b=-0.007$, $p<0.001$). The coefficient indicates that a 10 μg/m^3 increase in annual average NO_2 levels in one's LSOA is associated with a 0.07 decrease in life satisfaction (on a 1-7 Likert scale). The results relating to the control variables are consistent with existing research in these areas and so for parsimony are not discussed. To control for time-varying local characteristics reflective of economic activity and urbanisation, as well as green and blue space, we added in spatial control variables to our model (specification 2 in Table 2.2). This results in a significant reduction in the size of the NO_2 coefficient relative to that observed under specification 1 ($b=-0.004$, $p<0.001$). This highlights the importance of adding in spatial controls to capture differences in economic, social, and environmental conditions across neighbourhoods when estimating the relationship between air quality and life satisfaction. In other words, NO_2 is significantly correlated with these factors and in the absence of such controls, the NO_2 coefficient would partially reflect the effect of local socio-economic activity and land use more generally on subjective well-being.

Table 2.2. Full regression results with unstandardised coefficients.

Variable name	Model specifications				
	1: OLS - baseline	2: OLS - spatial controls	3: Fixed effects	4: IV First stage	4: IV Second stage
NO_2 ($\mu g/m^3$)	-0.007*** (0.001)	-0.004*** (0.001)	-0.003* (0.001)		-0.003* (0.002)
Annual household income (log equivalence)	0.093*** (0.006)	0.084*** (0.006)	0.024*** (0.006)	0.261*** (0.018)	0.084*** (0.004)
Age (years)	-0.028*** (0.001)	-0.028*** (0.001)	0.019* (0.010)	0.039*** (0.004)	-0.028*** (0.001)
Age-squared (years)	0.000*** (0.000)	0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Female (yes/no)	0.039*** (0.008)	0.038*** (0.008)	0.407 (0.256)	0.034 (0.023)	0.038*** (0.006)
University-level qualification (yes/no)	0.039*** (0.009)	0.030*** (0.009)	-0.002 (0.023)	0.494*** (0.026)	0.030*** (0.006)
Marital status (reference category: single)					
Married (yes/no)	0.276*** (0.013)	0.271*** (0.013)	0.158*** (0.026)	-0.310*** (0.037)	0.271*** (0.009)
Separated (yes/no)	-0.183*** (0.032)	-0.179*** (0.032)	-0.145*** (0.039)	-0.292*** (0.090)	-0.179*** (0.023)
Widowed (yes/no)	0.003 (0.023)	0.002 (0.023)	-0.091* (0.043)	-0.167** (0.064)	0.002 (0.016)
Divorced (yes/no)	-0.061** (0.021)	-0.059** (0.021)	-0.014 (0.035)	-0.722*** (0.056)	-0.059*** (0.014)
Living as a couple (yes/no)	0.218*** (0.014)	0.217*** (0.014)	0.206*** (0.021)	-0.657*** (0.042)	0.217*** (0.011)
Employment status (reference category: employed)					
Self-employed (yes/no)	0.024 (0.015)	0.021 (0.015)	0.028 (0.019)	-0.268*** (0.048)	0.021 (0.012)
Unemployed (yes/no)	-0.361*** (0.021)	-0.351*** (0.021)	-0.212*** (0.020)	0.433*** (0.066)	-0.351*** (0.017)
Retired	0.271***	0.268***	0.090***	0.010	0.268***

Variable name	Model specifications				
	1: OLS - baseline	2: OLS - spatial controls	3: Fixed effects	4: IV First stage	4: IV Second stage
(yes/no)	(0.019)	(0.019)	(0.021)	(0.059)	(0.015)
Caring for family (yes/no)	-0.021 (0.018)	-0.013 (0.018)	0.019 (0.019)	0.096 (0.059)	-0.013 (0.015)
In training (yes/no)	0.178*** (0.018)	0.172*** (0.018)	0.126*** (0.022)	0.433*** (0.063)	0.171*** (0.016)
Disabled (yes/no)	-0.708*** (0.031)	-0.692*** (0.031)	-0.356*** (0.029)	-0.404*** (0.076)	-0.691*** (0.019)
Other (yes/no)	-0.069 (0.070)	-0.068 (0.070)	-0.071 (0.064)	-0.292 (0.255)	-0.068 (0.064)
Health satisfaction (reference category: neither satisfied/unsatisfied to completely unsatisfied)					
Completely satisfied with health (yes/no)	1.777*** (0.012)	1.777*** (0.012)	1.292*** (0.012)	-0.035 (0.038)	1.777*** (0.010)
Very satisfied with health (yes/no)	1.323*** (0.009)	1.318*** (0.009)	0.966*** (0.008)	-0.088*** (0.026)	1.318*** (0.007)
Satisfied with health (yes/no)	0.833*** (0.009)	0.831*** (0.009)	0.609*** (0.009)	-0.012 (0.033)	0.831*** (0.008)
Commuting time (reference category: non-commuters)					
1-15 mins (yes/no)	0.025 (0.013)	0.024 (0.013)	0.017 (0.015)	-0.607*** (0.045)	0.024* (0.011)
16-30 mins (yes/no)	-0.002 (0.013)	-0.004 (0.013)	0.009 (0.015)	-0.033 (0.048)	-0.004 (0.012)
31-50 mins (yes/no)	-0.004 (0.016)	-0.004 (0.016)	0.023 (0.018)	0.383*** (0.057)	-0.005 (0.014)
>50 mins (yes/no)	-0.045** (0.017)	-0.046** (0.017)	0.006 (0.019)	0.550*** (0.059)	-0.047** (0.015)
Time variables					

Variable name	Model specifications				
	1: OLS - baseline	2: OLS - spatial controls	3: Fixed effects	4: IV First stage	4: IV Second stage
Year	-0.001 (0.008)	0.002 (0.008)	-0.011 (0.016)	0.085*** (0.022)	0.002 (0.006)
Wave	-0.014 (0.008)	-0.013 (0.008)	-0.024 (0.018)	-0.489*** (0.024)	-0.013* (0.006)
Spatial control variables					
Population density (people per km^2)		-0.000** (0.000)	0.000 (0.000)	0.001*** (0.000)	-0.000*** (0.000)
Crime deprivation		-0.008 (0.004)	-0.011 (0.007)	0.988*** (0.012)	-0.009* (0.004)
Income deprivation		-0.380*** (0.050)	-0.075 (0.085)	2.806*** (0.129)	-0.382*** (0.032)
Geographical deprivation		-0.000** (0.000)	-0.000** (0.000)	-0.009*** (0.000)	-0.000*** (0.000)
Area of greenspace (% of LSOA)		-0.000 (0.000)	0.001 (0.001)	-0.105*** (0.001)	-0.000 (0.000)
Area of water (% of LSOA)		-0.001 (0.001)	0.001 (0.001)	-0.064*** (0.002)	-0.001 (0.001)
Constant	6.649 (15.761)	-0.152 (15.855)	25.285 (32.675)	- 141.044*** (44.559)	-0.043 (11.165)
Instrumental variables					
Annual average daily traffic count				0.000*** (0.000)	
Road density per LSOA				2.226*** (0.258)	
Observations	199,602	199,602	199,602	199,602	199,602
Individuals			54,348		
R^2	0.28	0.28	0.20		0.28
F-statistic				12125.31	2343.64

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Despite the inclusion of a wide range of economic and geographic control variables, one may still be concerned that there are other sources of unobserved heterogeneity affecting the model estimates (e.g. personality traits). To address this concern, we take advantage of the panel nature of the dataset by using fixed effects (specification 3 in Table 2.2). The coefficient size for NO_2 from our fixed effects regression analysis falls slightly relative to that from our pooled cross-sectional model in specification 2 ($b=-0.003$, $p<0.05$). Here the coefficient indicates that a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.03 decrease in life satisfaction (on a 1-7 Likert scale).

How large are these effects?

An increasingly common method for communicating the welfare effects from exposure to air pollution, and indeed other environmental disamenities, when using the life satisfaction approach is to calculate compensating differentials. More specifically, by using the point estimates for income and the environmental variable of interest (e.g. NO_2) we can calculate constant trade-off ratios (Levinson 2012; Luechinger & Raschky 2009). In other words, how much extra income an individual would need to be compensated for the deterioration in air quality. This approach has previously been used to value the welfare losses associated with a diverse range of air pollutants such as PM_{10} (Ambrey *et al.* 2014; Ferreira *et al.* 2013; Levinson 2012; Mackerron & Mourato 2008), $PM_{2.5}$ (Zhang *et al.* 2017a), and SO_2 (Luechinger 2009). One limitation with this approach is endogeneity in income. That is, the effect of income on life satisfaction is likely to be significantly understated due to measurement error within the income variable. In addition, unobserved heterogeneity, such as working hours, time spent away from family and loved ones, and stress can also result in biased estimates for income (Powdthavee 2010). Failure to account for endogeneity in income would mean that any measures of the extent to which individuals are willing to trade off income for reductions in exposure to environmental disamenities such as NO_2 would likely be significantly biased upwards.

An alternative approach for communicating the 'psychological' cost associated with exposure to environmental disamenities such as NO_2, and one that we employ in this paper, is to compare the relative effects of NO_2 exposure on life satisfaction to that of other predictors of life satisfaction. Using this approach and looking at the coefficients in Table 2.2, the average loss in life satisfaction experienced from an annual average ambient level of 40 $\mu g/m^3$ which is the legal EU limit (and exceeded in many parts of the UK) would be comparable to that of many big-hitting life events. For instance, at this level of NO_2 pollution, the disutlity effects would amount to 56 per cent of the effect size of unemployment (relative to being employed), and 83 and 133 per cent of the effect size of marital separation and widowhood (relative to being single) respectively, factors commonly found to be important negative correlates with subjective well-being. If we now look at variables positively related with subjective well-being, the estimated disutility impact from NO_2 exceeds that of the estimated effect from being retired as opposed to being in full time unemployment (133%) and approximately three quarters of the effect size of being married as opposed to being single. All this suggests that the adverse effects of NO_2 are high relative to that of many other commonly observed correlates with subjective well-being.

The significant geographic differences in the level of NO_2 as illustrated in Figure 2.1 also suggest that there are significant geographic inequalities in the disutility impacts of NO_2. For example, average annual ambient levels of NO_2 range from approximately 3 μg/m^3 in the South West of England (Cornwall and Devon) to approximately 58 μg/m^3 in central London. This would imply that the average utility effects associated with NO_2 from living in Cornwall and Devon as opposed to central London would amount to just over three quarters of the effect size of being unemployed relative to being employed and exceed that of other significant life events such as marital separation and widowhood. Other locations where levels of NO_2 are particularly high include London Heathrow airport, Birmingham, Sheffield, and Southampton.

Robustness checks

Despite the inclusion of a broad array of time-variant spatial control variables (e.g. economic and social deprivation, population density and greenspace) and our use of fixed effects, (thereby controlling for time-invariant heterogeneity), we recognise that there is still the potential for other sources of endogeneity to affect our regression estimates. For instance, despite our use of a relatively spatially disaggregated dataset, it is possible that measurement error could bias our regression estimates. Such measurement error would bias our estimated effect of NO_2 on life satisfaction downwards. On the other hand, the NO_2 coefficient could partly be capturing the effect of other air pollutants such as PM_{10}. Such omitted variable bias would bias our estimates upwards. To test if endogeneity is significantly affecting our model estimates we adopted an instrumental variables approach. Specifically, we instrument NO_2 with annual average daily traffic flow (AADF) counts and road density per

LSOA. We expect that major road traffic flow and road density, both recorded at the LSOA level, will be related to NO_2 levels but not directly related with life satisfaction, after conditioning on our control varibables such as economic and social deprivation, population density and commuting patterns.

AADF counts are maintained by the Department for Transport and measure street-level traffic counts for every A-road and motorway in Great Britain. We calculated average values for each LSOA in England by using the Spatial Join tool in ArcGIS. Road density was calculated using the road layers available in Ordnance Survey's Meridian 2 dataset. This is a vector dataset of Great Britain at a 1:50,000 scale and contains detailed spatial information about motorways, A-roads, B-roads, and minor roads. We used the Spatial Join tool in ArcGIS to calculate the length of all roads per LSOA and then divided this by LSOA area to generate a comparable unit across LSOAs.

We expect that major road traffic flow and road density, both recorded at the LSOA level, will be related to NO_2 levels but not directly related with subjective well-being. We found a significant direct correlation between our instruments and NO_2 (r=0.208 and 0.584) but no significant direct correlation between our instruments and subjective well-being (r=-0.004 and -0.056). Perhaps one could argue that there could be indirect effects in that traffic and road density will be related with factors such as commuting patterns, population density, noise and congestion which in turn could be related with subjective well-being. However, we control for the indirect channels through which one could argue that traffic flow and road density could plausibly affect subjective well-being, e.g. population density, commuting patterns, economic and social conditions within the neighbourhood are all control variables in the regression analysis. The question then becomes whether, after conditioning on these control variables, is it reasonable to expect that traffic flow and road density within the neighbourhood will still affect their subjective well-being? We argue that it is reasonable to expect that it should not.

All the instruments have the expected positive and statistically significant relationship with NO_2 and in all cases the statistical tests suggest that the instruments are relevant. The Anderson canonical correlations likelihood ratio test, for instance, rejects the null of underidentification and the obtained F statistic (F-statistic =12125) exceeds the conventional minimum standard of power of F = 10 (Stock *et al.* 2002). We can test the validity of the instruments, conditioning on the assumption that a subset of the instrument is valid, by implementing the standard overidentification test. The resulting Sargan's test statistic was statistically insignificant with a p value of 0.72 and therefore we can be reasonably satisfied that our instruments are consistent in producing robust estimates of the relationship between NO_2 and life satisfaction. The results relating to our instrumental variable analysis can be seen in Table 2.2 (specification 3). We can see that our instrumented NO_2 coefficient ($b=-0.003$, $p<0.005$) was not significantly different from that obtained from our fixed effects model which suggests that any remaining sources of endogeneity unaccounted for through our use of fixed effects and our detailed set of spatial and individual controls is not affecting our model estimates to a significant degree.

2.5 Discussion

Policymakers are becoming increasingly supportive of using subjective well-being data for formulating public policy. In 2012, for instance, the UK's Office for National Statistics published its first index of subjective well-being, as part of the government's Measuring National Well-Being project. This index provides evidence for the national state of quality of life and is used across UK government to drive decision-making and policy analysis. Additionally, the UK Department for Environment, Food and Rural Affairs (DEFRA) use subjective well-being data to evaluate the Nature Improvement Areas scheme and the Department for International Development (DFID) leads on how best to use subjective well-being evidence to measure different dimensions of progress (Cabinet Office 2013). The UK has also officially backed the United Nation's Sustainable Development Goals (SDGs) which, among other things, strive for good health and well-being (SDG 3). The use of subjective well-being measures is therefore used widely across UK government to better understand society's welfare and as such the ability to understand and quantify factors that affect these measures is important.

This study focused on ascertaining the disutility effects from NO_2 by matching data relating to individuals' subjective well-being from twelve waves of the British Household Panel Survey (BHPS) and the UK Household Longitudinal Survey (UKHLS) with annual ambient air pollution data from DEFRA. To mitigate concerns about unobserved local characteristics correlated with both life satisfaction and NO_2 biasing our fixed effects regression estimates, we matched these data sources with a wide array of external geo-referenced environmental datasets capturing differences in economic, social, and environmental conditions across neighbourhoods. To the best of our knowledge, it is the first study that couples spatially disaggregated longitudinal household survey and air pollution data with a range of spatial controls when examining the relationship between NO_2 and subjective well-being. Our results serve to highlight how failure to include spatial controls reflective of the wider economic, social, and environmental conditions in the neighbourhood could give rise to significant omitted variable bias when examining the relationship between indicators of environmental quality such as NO_2 and life satisfaction.

We find a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.03 decrease in life satisfaction (on a 1-7 Likert scale). To help put these findings into perspective, we compared this effect size to that of many other widely studied determinants of subjective well-being. Our results suggest that the adverse effects of NO_2 are high relative to that of many other commonly observed correlates with psychological well-being. For example, the estimated disutility effect from an average annual ambient level of 40 $\mu g/m^3$ which is the legal EU limit (and exceeded in many parts of the UK) would be comparable to that of many big-hitting life events such as unemployment, marital separation, and widowhood. These findings support much of the epidemiological literature which suggests that exposure to NO_2 can have a substantive detrimental effect on health (Brook *et al.* 2010; Brunekreef *et al.* 2015; Shah *et al.* 2015)(Brook *et al.* 2010; Brunekreef *et al.* 2015; Shah *et al.* 2015) which will of course in turn affect individuals' subjective well-being. There is also an emerging body of epidemiological research to suggest that air pollution may affect mental and cognitive health (Power *et al.* 2016; Tzivian *et al.* 2015). Exposure to NO_2 is likely to have a negative aesthetic effect for many (e.g. through sight, smell and even taste), which again is likely to affect subjective well-being. Finally, concern for one's health and that of one's family, as well as concern for the environment, may too have a negative effect on subjective well-being.

It is also interesting to note the significant geographic differences in the distribution of NO_2. The highest annual levels occur in London and the lowest in regions of South West England. One avenue for future work would be to go beyond looking at geographic differences and explore if there are any socio-economic or demographic inequalities in exposure, and beyond that, how inequalities in well-being at small-scale geographies are associated with environmental features. Furthermore, the consideration of equity and 'who to prioritise' when using subjective well-being data in public policy-making is out of the scope of this paper, but should be an important consideration when designing intervention strategies (Institute of Economic Affairs 2012).

One limitation of this work and indeed all work concerned with estimating the effect of environmental amenities on subjective well-being surrounds the potential for endogeneity bias to affect the model estimates. Relative to previous work concerned with estimating the disutility effects of NO_2 this work has, however, a number of advantages such as its longitudinal nature and the suite of spatial controls employed. Still, we recognise there is the potential for other sources of endogeneity to affect our estimates. We employed an instrumental variables technique to account for any remaining sources of endogeneity but as always with analysis of this nature, there is a concern surrounding instrument validity.

There is no significant direct correlation between our instruments and subjective well-being and they pass the standard validity checks and we also argue that any potential indirect channels though which they could affect subjective well-being are accounted for in the model specification.

One useful avenue for future work would be to further refine the identification of the effect of NO2 and indeed other environmental disamenities in any micro-econometric analysis of subjective well-being through the use of additional instruments or quasi-experimental approaches when data allows. Previous work suggests multiple potential exposures related to urban form contribute to the apparent relationship between air pollution and health and well-being effects, for example noise and heat (Brauer & Hystad 2014). Noise is highly collinear with air pollution and potentially a more direct route to well-being and mental health outcomes (Tzivian *et al.* 2015). Green- and bluespaces have also been shown to buffer against air pollution, noise, and urban heat (Dadvand *et al.* 2014; Dadvand & Nieuwenhuijsen 2019). Given the possible residual confounding from these multiple exposures, future research should examine joint exposure effects to better capture the relationship with well-being. Better still, studies could address the likely highly spatially correlated nature of these variables by developing latent constructs of healthy urban forms (Brauer & Hystad 2014).

Finally, to conclude, our results suggest that the welfare effects, as proxied by subjective well-being, from NO_2 can be substantive. For instance, our analysis suggests that the disutility experienced by NO_2 may be broadly comparable to that of many major life events such as unemployment, separation, and widowhood. Moreover, given that the effects of NO_2 on life satisfaction are population-wide (i.e. to some extent everyone is exposed to NO_2, whereas only a fraction of the population are unemployed or separated), this suggests that the benefits to society from any reductions in NO_2 would be substantive.

Chapter 3: One size does not fit all: how type of urban open space matters when exploring the link with well-being

3.1 Abstract

A growing body of evidence suggests that residential proximity to open spaces is beneficial for human health and well-being. However, very few studies use existing and consistent open space typologies to examine this relationship. This is particularly important for urban planners, who require clear guidance and terminology. Here we used the Planning Policy Guidance Note 17 (PPG17): *Planning for open space, sports and recreation*, a formal open space typology used across the UK for land use planning guidance, to categorise open spaces in Greater London, UK. The typology contains 11 categories (e.g. Parks and gardens and Amenity greenspace), and 41 nested subcategories (e.g. Rivers and Community gardens). We spatially linked the residential quantity of open space categories with individuals in the British Household Panel Survey and the UK Household Longitudinal Study, two large, longitudinal panel surveys. We used fixed effects regression to explore the relationship between three subjective well-being measures (life satisfaction, mental health and self-reported general health) and residential open space. We used a suite of individual, household and neighbourhood level variables to control for confounding effects. We found Golf courses, Allotments, Playing fields, Equestrian centres and Other had the largest positive median effect sizes (β=0.036 to 0.055), surprisingly Village greens, Country parks, Amenity green space and Nature reserves had the largest negative median effect sizes (β=-0.051 to -0.485). All three bluespace categories were assoicated with higher levels of well-being (Canals, Reservoirs and Rivers). We found the PPG17 typology problematic when assessing the well-being benefits of open spaces, due to the broad nature of the higher categories. Our findings are important for future research, they highlight that urban green- and bluespaces are heterogenic i.e. not all greenspaces are equal. Our findings are also important for any future considerations in designing a new open space planning typology; for example, they demonstrate the need for disaggregating green- and bluespace. They highlight that bluespaces should be identified separately from greenspaces, and that the localised context of land uses, such as the likely beneficiaries and the specific mechanisms that deliver these benefits, must be considered in future work.

3.2 Introduction

Proximity and exposure to the natural environment have been found to be beneficial for human health and well-being (Barton & Pretty 2010; Maas *et al.* 2006; Mitchell & Popham 2008). This is particularly important in urban environments, where environmental 'bads' such as air pollution and noise have been attributed to poor health (Dadvand *et al.* 2015; Nowak *et al.* 2014; Tzivian *et al.* 2015). Improving the provision of open and natural spaces in urban areas has the potential to not only abate the effects of poor environmental quality, but also to provide positive health and well-being benefits directly (van den Bosch & Nieuwenhuijsen 2017). With two-thirds of the global human population estimated to be living in urban environments by 2050 (World Health Organisation 2016), better understanding how to design and improve open and natural environments in urban areas is increasingly important.

However, despite much research indicating a positive relationship between well-being and the natural environment, there are also studies that find little or no association at all. One possible explanation for the discrepancies between findings could be in how open environments are defined and categorised (Hunter & Luck 2015; Lai *et al.* 2019). For example, in the majority of studies to date, research has focussed on green/bluespace as a homogeneous category, grouped together as one category 'open', 'natural', 'green' or 'blue' space (Olsen *et al.* 2019; Wheeler *et al.* 2015). It is possible that by amalgamating types of open and natural environment into a homogenous unit, researchers may be missing the different characteristics of these spaces that underpin the relationship between the natural environment and human health and well-being. Indeed many recent studies recommend that future work should focus on identifying the different types of 'green' and 'blue' that are associated with specific health and well-being benefits (Akpinar *et al.* 2016; Hartig *et al.* 2014; Wheeler *et al.* 2015). Examining how different types of open, green and blue spaces affect human well-being will also help us to better understand the pathways through which these influences occur.

With a few exceptions, much of the research in this area is cross-sectional in its design, which while providing an important contribution to our understanding, has acknowledged limitations in its analytical capability to infer causality (Houlden *et al.* 2018). Using time-series data instead of cross-sectional data allows us to better control for potential sources of endogeneity. Several studies have also highlighted the need for future research to identify how the natural environment affects different aspects of an individual's health and well-being (Gascon *et al.* 2015). For example, it is likely that the well-being benefits and the pathways to these will differ across open space characteristics and uses (Dzhambov *et al.* 2020).

Very few studies use existing and consistent open space typologies to examine the relationship with well-being (Douglas *et al.* 2017). The UK government uses a formal open space typology for land use planning guidance, and this is used by every local authority to design and assess its land use strategy. The Planning Policy Guidance Note 17 (PPG17): *Planning for open space, sports and recreation* was created in 1991 and republished in 2002, and specifically states that planning and managing green space is beneficial for human well-being (Office of the Deputy Prime Minister 2002). The PPG17 consists of 11 land use categories, including Parks and gardens, Natural and semi-natural urban greenspace, Cemeteries and churchyards and Outdoor sports facilities, and 41 subcategories nested within these. It encourages all local authorities to complete an open space audit, assess demand for green space, and produce a strategy for open space provision. In 2008, it was estimated that over 90% of local authorities in England either had an open space strategy, or were in the process of developing one (Natural England 2008). The PPG17 was replaced by the National Planning Policy Framework in 2012 and has recently been revised in early 2019, but so far there has been no revision or replacement of the PPG17 land use typology. The new framework highlights the need for land use planning to enhance well-being through the provision of open space.

Despite this land use typology being used nationally, to the best of our knowledge there is only one other study that explores how the different types of open space in this typology are related to human well-being. This study, conducted by Houlden et al., (2019a) only used three of the categories in the typology, so this study builds upon this by exploring the full set of categories and subcategories in the typology. Given that there is no standardised green- and bluespace typology used for research purposes, we use this existing, highly-detailed and accurate typology to differentiate open spaces.

3.2.1 Types of open space and well-being

Several studies have used existing land use datasets to attempt to identify if different types of 'green' and 'blue' are associated with well-being. For example Klompmaker et al., (2018) categorised land parcels as urban green, agricultural green or natural green for The Netherlands. They found that natural green was associated with lower levels of obesity and higher levels of physical activity, with the relationships reversed for urban green. Pasanen et al., (2019) found a positive relationship between mental health and residential bluespace in England (measured as freshwater coverage from the UK Land Cover Map 2007), but they only differentiated between coastal and freshwater, and not between different types of bluespace.

However, other studies do not find these associations. For example, Bos et al., (2016) use the Dutch Land Use Database to find green space in The Netherlands. The database identifies land parcels as urban green (e.g. vegetable gardens, sports and recreation areas and parks), agricultural green and natural green, yet they group all of these categories together and refer only to green space. They found in the majority of their models a small or non-significant relationship between green space and mental health. Triguero-Mas et al., (2017) used the Urban Atlas 2006 and the Top10NL land registry dataset to map green and bluespace in four European cities. They group together urban green areas, agricultural/semi-natural/wetland areas, and natural forest/plantations to refer to green space, and water bodies as bluespace. They also did not find any relationship with mental health. Akpinar et al., (2016) used one total green space category and five subcategories in the US National Land Cover Data (urban green space, forest, rangeland, agricultural land, and wetland) to explore the effects on the number of mental health complaints in the last 30 days, anxiety-depression complaints in the last 2 weeks, and self-reported general health in a sample population in Washington State, USA. In urban areas they found no relationship between total greenspace and all three measures of well-being. They only found a significant association with mental health complaints and urban green space and forest cover, where zip-codes with increased urban green space and forest cover were related with fewer days of mental health complaints. There were no other significant relationships.

A number of studies have since attempted to identify the specific characteristics of urban natural environments that are important for health and well-being. These have been largely focussed on identifying features of open natural spaces that may affect human well-being through well-documented human-nature pathways. For example, if an open space type encourages physical activity, recreation, or opportunities for social cohesion or nature conservation. Wood et al., (2017) used a green space dataset for Perth, Australia to identify the number of recreation, sport and nature features contained within urban parks. They found a significant positive relationship between the number of features in parks within residential neighbourhoods and mental health. Francis et al., (2012) found features or specific use types (walking paths, shade, water features, irrigated lawn, birdlife, lighting, sports facilities, playgrounds, type of surrounding road, and presence of nearby water) of residential public open space to be more important for mental health of residents than quantity of open space in Perth, Australia. Coombes et al., (2010) found 'formal green spaces' had higher visitation rates for physical activity in Bristol, UK, suggesting that this is because this category of natural space is characterised by a good path network and is well maintained. Tsai et al., (2016) found greater forest edge density and larger herbaceous patch size in large U.S. urban areas were associated with higher levels of physical activity. Allotment use has been associated with greater levels of physical activity and well-being, especially in older age (van den Berg *et al.* 2010b). Allotments represent a specific type of urban green space, characterised by human use, physical activity and social cohesion (van den Berg *et al.* 2010b).

3.2.2 Open spaces and urban planning

The recognition of the salutogenic benefits of the natural environment, particularly in urban areas, is reflected in the recent increase of broad global agreements to address the quality and provision of urban green and bluespaces in relation to human health. For example, the UN Sustainable Development Goals aim for universal access to good quality and accessible green spaces in cities by 2030 (United Nations 2017). The World Health Organisation's European Healthy Cities Network sets out a vision for physical environments that enable and drive health and well-being for all (World Health Organisation 2018). At a national level, one of the six key policy areas in the UK government's 25 Year Environment Plan is to connect people to nature to improve health and well-being (HM Government 2018).

However there is very little consistent information regarding how to implement these broad statements about green space provision, quality and exposure, and it is often therefore left open to interpretation (Douglas *et al.* 2017). Byrne et al., (2010) provide a thorough review of greenspace planning in densifying urban areas. They highlight that internationally many greenspace quantitative 'standards' have been used by planners to provide open spaces in urban areas, but that these standards have rarely been robustly tested, and are often not even implemented. They stress that quantitative criteria without quality and access criteria often leads to poorly designed greenspace, which will have implications for the potential well-being benefits provided. Douglas et al., (2017) highlight the need for research findings to be better targeted for urban planners, so that future design interventions can reflect this growing body of research. Using an established and nationally recognised land use typology has the benefit of attempting to link research directly with land use planners. Gaining a better understanding of how different land use types relate with well-being is an important first step.

3.2.3 Key questions and approach

To address the issues of a lack of a consistent and existing open space typology in the well-being and nature literature, and the difficultly for this research to be useful for land use planning, in this study we ask the following questions:

1. Are there open space categories and subcategories in the PPG17 that are particularly beneficial or deleterious for the well-being of residents?
2. Is the PPG17 typology useful for understanding how different components of open space contribute to well-being?

We use a highly detailed and up-to-date open space PPG17 dataset in London, UK to give us locations and categorisations of all open spaces in the city. London is ranked tenth across 30 global cities, by public greenspace percentage area per capita (World Cities Culture Forum 2017). In July 2019, London became the world's first National Park City. This makes it a particularly interesting urban area to study as it has a current agenda to improve the provision and use of its open spaces. Additionally, Greater London is a large and densely populated city; London's land area represents only 0.65% of the UK's total land area but is home to 13.36% of the UK's total population. This provides a large sample population to study, and as the city also maintains freely available, spatially accurate and up-to-date open space dataset, it is an attractive case study. We spatially link these data with two large longitudinal panel datasets, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), using the residential location for each individual. Despite both surveys designed to be nationally representative, there are important differences in their spatial structure, demographic composition (due to differential rates of attrition), and time period of data collection. Using two different surveys allows us to examine these different population samples and time periods, and to explore the impact that these differences have on the relationships between well-being and the natural environment.

We also use three measures of subjective well-being in our analysis. There is a large body of research that examines the reliability and validity of measures of subjective well-being (Diener *et al.* 2013; Frey *et al.* 2010). Despite several potential limitations, subjective measures of well-being have been shown to have a high scientific standard in terms of internal consistency, reliability and validity (Frey *et al.* 2010; OECD 2013). Life satisfaction, mental health and general health are all commonly used measures in well-being surveys, and well-being and nature literature (e.g. Mears et al., 2019; Pasanen et al., 2019; White et al., 2013b). The General Health Questionnaire (GHQ) is a screening tool which helps to diagnose mood disorders. It is widely used in literature as a measure of mental health (Gascon *et al.* 2015). We make use of a suite of socio-demographic and spatial explanatory variables available to us, both in the survey data and that which is publicly available, to address our research questions.

3.3 Methods

3.3.1 Study area

London is the capital and largest city in the UK, and Greater London covers an area of 1,572 km^2. Greater London, or the Greater London Built-up Area, is often used for administrative statistics and refers to the continuous urban area. This includes the City of London, 12 London boroughs, and 20 Outer London boroughs. In 2019, the UK Office for National Statistics (ONS) estimated Greater London's population at 8.962 million, with a mean population density of 5,701 individuals per km^2 (Office for National Statistics 2020a).

3.3.2 Planning Policy Guidance Note 17 (PPG17)

We use the Greenspace Information for Greater London (GiGL) Open Space Sites dataset to identify all PPG17 categorisations of open spaces in Greater London (downloaded 12th December 2018; Figure 3.1). GiGL manage and maintain all data relating to the natural environment for Greater London for regulatory and research purposes. Open space is defined as "undeveloped land which has an amenity value or has potential for an amenity value. The value could be visual, derive from a site's historical or cultural interest or from the enjoyment of the facilities it provides. It includes both public and private spaces but excludes private gardens" (GiGL 2020). The open spaces database is collated from submissions from each London Borough pertaining to the open spaces in their jurisdiction.

Open space sites cover 37% of the total area of Greater London (Figure 3.2). The PPG17 typology consists of 11 open space categories, and 41 nested primary use subcategories (Table 3.1). The database contains 12,631 open space polygons in Greater London (see Table S3.1 in appendix). All 425 polygons with no PPG17 category were removed from the main category analysis (12,206 open space sites). A further 22 polygons with no PPG17 subcategory were removed from the subcategory analysis (12,184 open space sites).

We also created different subsets of the dataset to enable us to further explore the potential importance of certain open space characteristics. This also allowed us to address any possible problems with small sample sizes in certain land use categories, and to better categorise bluespaces. We produced a 'green and blue open spaces only' layer by removing all primary use categories that were likely to have very little or no green/blue cover (Adventure playground, Civic/market square, Disused quarry/gravelpit, Land reclamation, Other Hard surfaces, Sewage/water works and Youth area). Disused quarry/gravelpits may be water filled but we could not identify which were and which were not, so it was assumed all were not. We also created a bluespace layer using the three subcategories defined by surface water (Canal, Reservoir, and River), and a green space only layer (removing the bluespace categories from the green and bluespace layer).

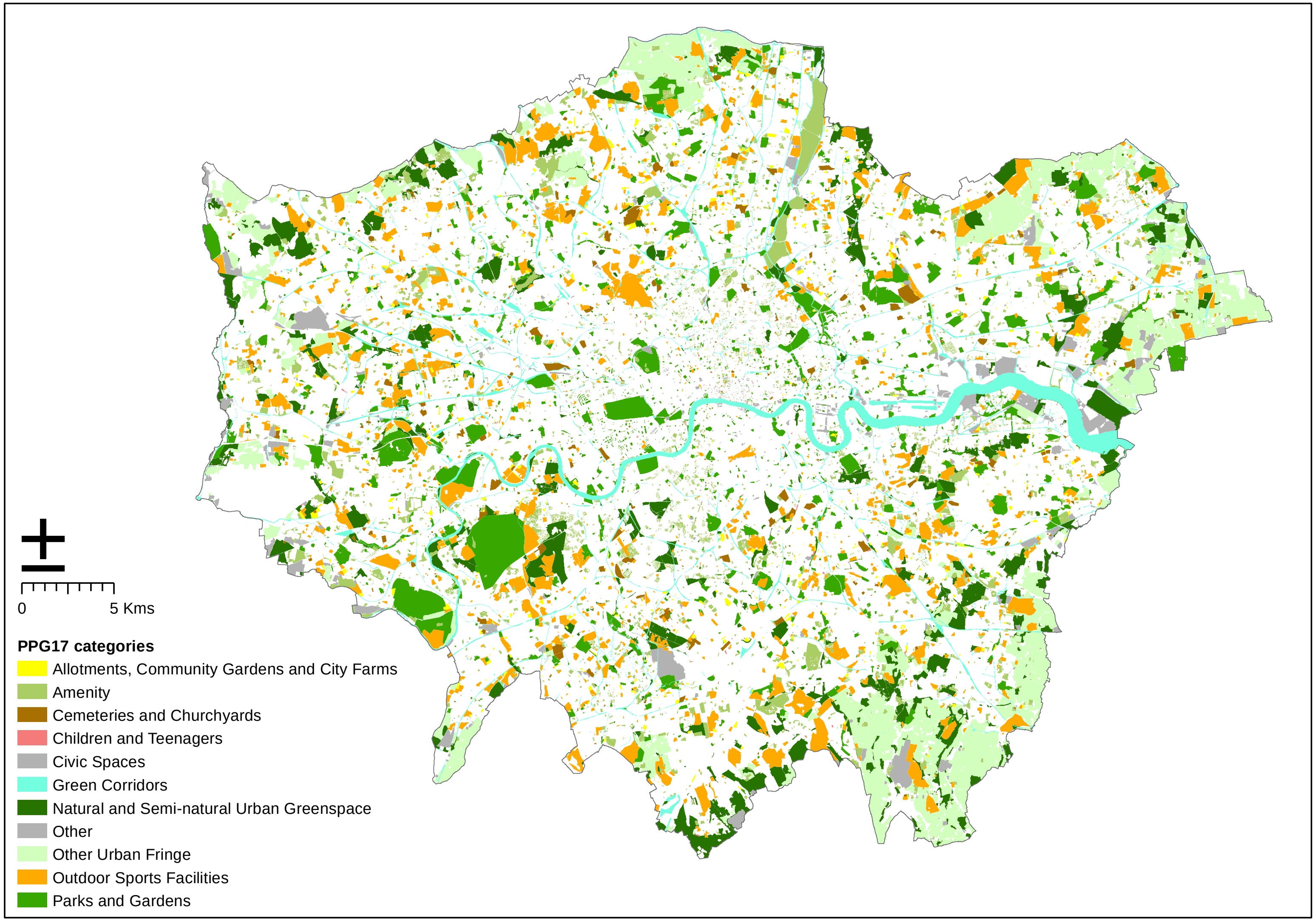

Figure 3.1. PPG17 categories of Greater London, as maintained by Greenspace Information for Greater London CIC (GiGL) [obtained 12th December 2019].

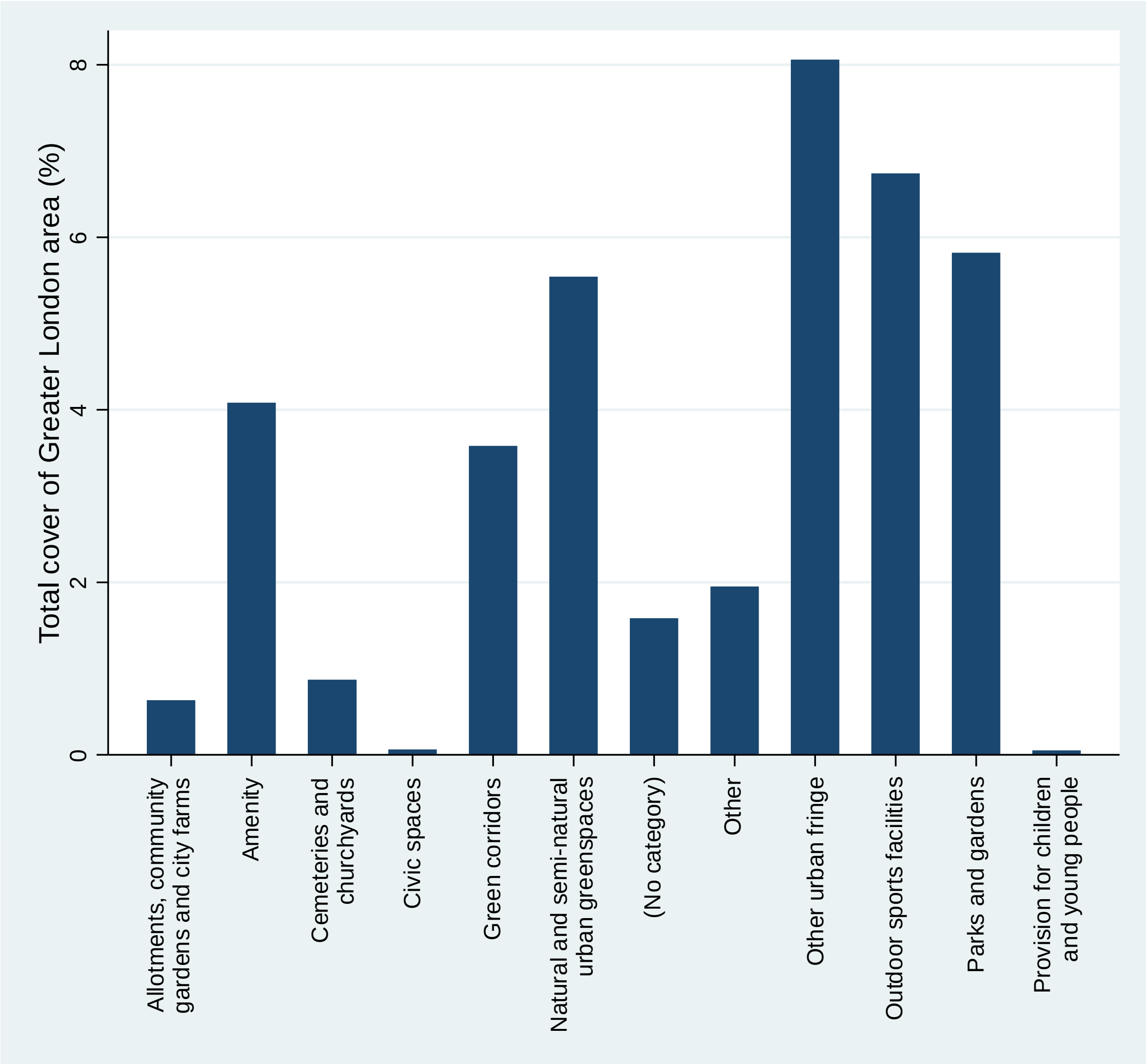

Figure 3.2. The total area of each PPG17 category, as a percentage of the total area of Greater London (calculated using the GiGL Open Space Sites (OSS) dataset).

Table 3.1. Planning Policy Guidance 17: Planning for Open Space, Sport and Recreation categories and primary use subcategories, and a description of each land use type. (1. (Office of the Deputy Prime Minister 2002), 2.(Greenspace Information for Greater London CIC 2017)).

PPG17 category	Description of use (1)	Primary use subcategories	Description of use (2)
Parks and gardens	Accessible, high quality opportunities for informal recreation and community events	Park	Traditional public open space laid out formally for leisure and recreation. They usually include a mixture of lakes, ponds, lidos, woodland, flowerbeds, shrubs, ornamental trees, play spaces, formal and informal pitches, bowling greens, tennis courts, golf pitch & put, footpaths, bandstands, toilets, cafes, and car parks – but not necessarily all of these. Parts of some parks might be managed as so-called natural areas.
		Formal garden	Well defined boundaries that display high standards of horticulture with intricate and detailed landscaping.
Natural and semi-natural urban greenspaces (inc. urban woodland	Wildlife conservation, biodiversity and environmental education and awareness	Common	Formal designation. Publicly accessible open space with few if any 'facilities'.
		Country Parks	Large areas set aside for informal countryside recreation near or within towns and cities.
		Private woodland	Woodland which is not accessible for recreational use, nor managed for nature conservation.
		Public woodland	Woodland which is accessible for recreational use, but not managed for nature conservation.
		Nature reserve	Open space managed primarily for nature conservation.
Green corridors	Walking, cycling or horse-riding, whether for leisure purpose or travel, and opportunities for wildlife migration	River	Rivers and streams that do not form part of any other land use, such as park, common or nature reserve.
		Canal	Artificial waterway that is navigable.
		Railway cutting	
		Railway embankment	
		Disused railway/trackbed	Categorised by its former use. If managed for nature conservation, it is termed nature reserve.
		Road island/verge	
		Walking/cycling route	

PPG17 category	Description of use (1)	Primary use subcategories	Description of use (2)
Outdoor sports facilities	Participation in outdoor sports, such as pitch sports, tennis, bowls, athletics, or countryside and water sports	Recreation ground	An area of mown grass used primarily for informal and unorganised ball games and similar activities.
		Playing field	Site comprised of playing pitches for organised team sports (football, rugby, hockey, cricket), often with changing rooms and a pavilion.
		Golf course	
		Other recreational	Site used predominantly for other organised team sports, such as bowls or tennis.
Amenity	Opportunities for informal activities close to home or work or enhancement of the appearance of residential or other areas	Amenity green space	Expanse of grass used for informal recreation. Few, if any, facilities.
		Village green	Formal designation, expanse of grass in the centre of old villages, often used in the summer for cricket.
		Hospital	Grounds of any clinic or health centre
		Educational	School, college, or field studies centre grounds where education is the primary function.
		Landscaping around premises	Communal amenity space around housing estates and community centres, and landscaping around industrial premises.
		Reservoir	If these form part of a park, categorise as park.
Provision for children and young people	Areas designated primarily for play and social interaction involving children and young people, such as equipped play areas, ball courts, skateboard areas, and teenage shelters	Play space	Site set aside for children, containing swings, slides and a roundabout etc.
		Adventure playground	Defined play area for children in a supervised environment. Boundaries and entrances are secure.
		Youth area	Defined area for teenagers including skateboard parks, outdoor basketball hoops, and more informal areas such as 'hanging out' areas and teenage shelters.
Allotments, community gardens and city farms	Opportunities for those people who wish to do so to grow their own produce as part of the long term promotion of sustainability, health and social inclusion	Allotments	
		Community garden	Generally maintained and managed by the local population as a garden and/or for food growing, and are normally restricted in access.
		City farm	Generally maintained and managed as a small farm by the local population. They contain livestock and planting and are normally restricted in access.

PPG17 category	Description of use (1)	Primary use subcategories	Description of use (2)
Cemeteries and churchyards	Quiet contemplation and burial of the dead, often linked to the promotion of wildlife conservation and biodiversity	Cemetery/churchyard	Burial grounds, graveyards, crematorium grounds and memorial gardens, and gardens and grounds of non-Christian places of worship
Other urban fringe		Equestrian centre	Intensive horse keeping and riding, but not extensive horse grazing (which would be agriculture)
		Agriculture	Arable and grazing land, including horse grazing and market gardening.
		Nursery /horticulture	This does not include commercial retail nurseries. Horticulture includes permanent glasshouses.
Civic spaces	Providing a setting for civic buildings, public demonstrations and community events	Civic/market square	Tarmac areas or paved open spaces, which may or may not include planting. Often provide a setting for civic buildings and opportunities for open air markets, demonstrations and civic events.
		Other hard surfaced areas	Areas designated for pedestrians. Typically used as 'sitting out' areas, and usually have seating/benches.
Other		Sewage/water works	Extensive sludge drying areas, filter beds etc.
		Disused quarry/gravel pit	May or may not be water filled.
		Vacant land	Land with no formal use. This includes many urban commons which are used for informal recreation and may be valuable for nature conservation, but have no formalised access or management for nature conservation.
		Land reclamation	Land recently decontaminated, or reclaimed from disuse, which has not yet been redeveloped.
		Other	Anything that does not fit above, such as air fields.

3.3.3 Survey data

We use two different longitudinal panel datasets, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), which are both available as part of the Understanding Society project (University of Essex. Institute for Social and Economic Research 2018). The BHPS and UKHLS are large multi-year panel surveys collecting individual and household information from a representative UK sample population. Demographic, socio-economic, health and geographic data are collected in the dataset, as well as that pertaining to attitudes, opinions and values. The BHPS ran from 1991 to 2008 (waves 1-18) and collected information from over 10,000 individuals (5000 households). Data collection for each wave in the BHPS was undertaken within a single year. The UKHLS has run from 2009 to the present day (waves 1-8 were available when writing) and collects information from over 50,000 individuals (40,000 households). Data collection for each wave in the US was undertaken over an overlapping two-year window.

Each individual in the BHPS and UKHLS has a geographic identifier to a lower super output area (LSOA). We used all individuals with LSOA codes pertaining to Greater London in this study (4,765 LSOAs in London). LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). The mean area of a London LSOA is 3.3 km^2 (the mean LSOA area in England is 4 km^2). Due to population fluctuations, approximately 5% of LSOAs in the UK changed in 2011 (split, merged or deleted), therefore for consistency we use the 2002 LSOA structure for all years.

3.3.4 Well-being measures

We use three measures of subjective well-being: life satisfaction, the General Health Questionnaire (GHQ) and self-reported general health. All three measures are captured in both the BHPS and the UKHLS and are consistent across the two surveys (Figure 3.3). Life satisfaction is based on the respondents' answer to the following question: 'How dissatisfied or satisfied are you with life overall?' Respondents give a single reply from a Likert scale with options ranging from 7 ('completed satisfied') to 1 ('completely unsatisfied').

In this study we use the 12-item short form of the GHQ. Respondents are asked to self-assess against six positive and six negative statements (e.g. I am capable of making decisions and I think of myself as worthless). Respondents give a single reply to each statement on a four-point scale, based on their own evaluation of how the “past few weeks” compare with “usual”. The scale ranges from 0 (not at all), 1 (no more than usual), 2 (rather more than usual) and 3 (much more than usual). This gives on overall score ranging from 0 (very low mental distress) to 36 (very high mental distress).

Self-reported general health is captured in both the BHPS and the UKHLS but the question slightly differs between them. In the BHPS, respondents are asked “Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been…?” In the UKHLS, respondents are asked “In general, would you say your health is…?” In both surveys the respondent gives a single answer from a Likert scale ranging from 1 (excellent) to 5 (very poor). In this analysis we inverted the scale, so that 5 reflected excellent health and 1 with very poor health, for ease of interpretation. In the UKHLS waves 1-5 the question is in the main interview survey, in waves 6-8 it is asked in the self-complete section.

The GHQ was asked in all 18 waves of the BHPS and all 8 waves of the UKHLS, but the life satisfaction question was only asked in the final 12 BHPS waves and all 8 UKHLS waves, and general health in 17 BHPS waves and all 8 UKHLS waves. Therefore, the number of observations in the life satisfaction and general health models for the BHPS is lower than that for the GHQ. For the BHPS analyses, life satisfaction includes 8,551 observations from 1,614 individuals (mean of 5.3 observations per person), GHQ includes 13,721 observations from 2,165 individuals (mean of 6.3 observations per person) and General Health includes 13,166 observations from 2,185 individuals (mean of 6 observations per person). For the UKHLS analyses, life satisfaction includes 34,646 observations from 10,795 individuals (mean of 3.2 observations per person), GHQ includes 36,028 observations from 11,349 (mean of 3.2 observations per person), and General Health includes 42,198 observations from 12,655 individuals (mean of 3.3 observations per person).

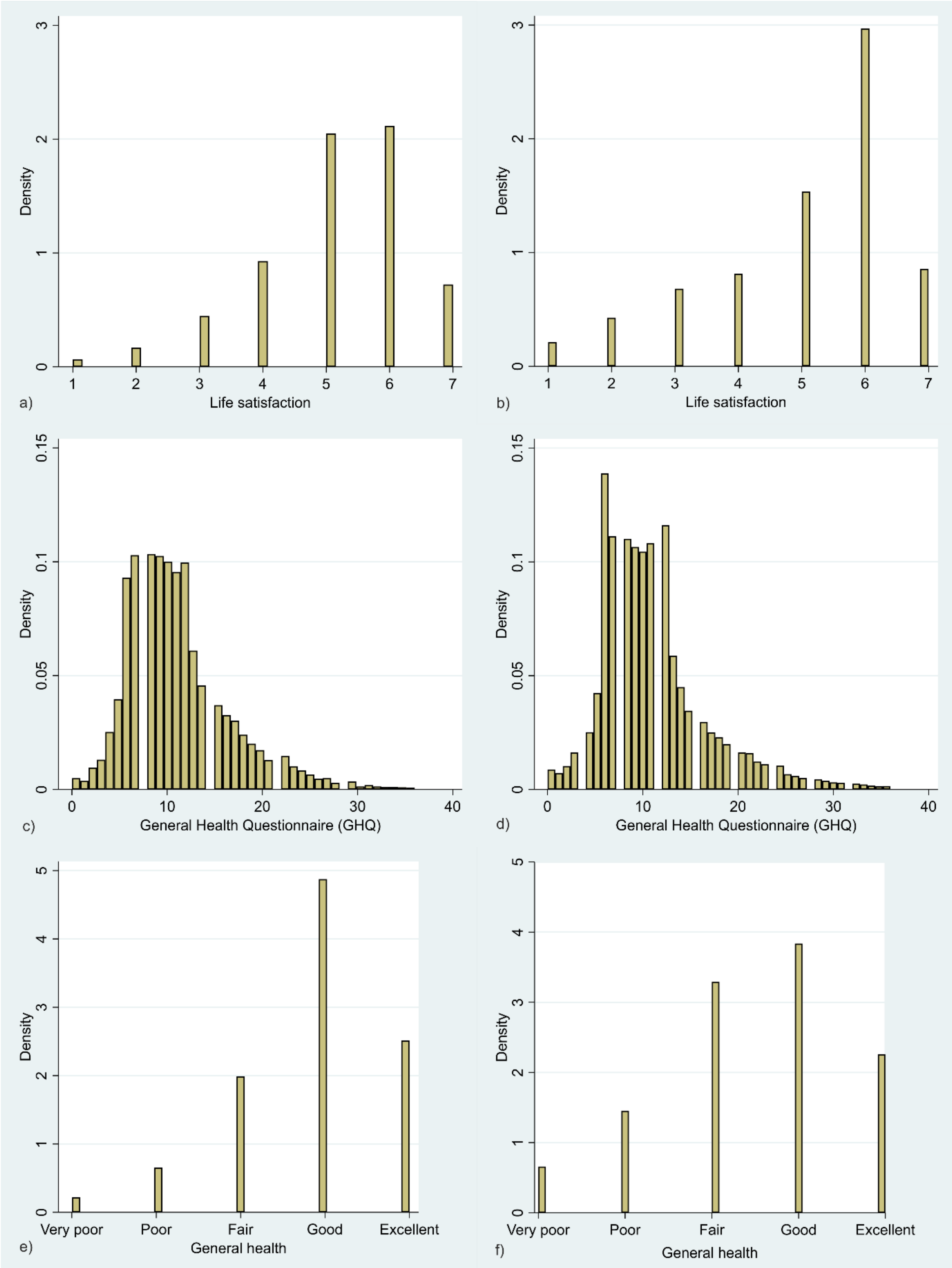

Figure 3.3. The distribution of subjective well-being across the population samples (BHPS: a, c and e; UKHLS: b, d, and f). The y-axis represents the density of observations per bin: the height of the bars are scaled so that the sum of their areas equals 1.

3.3.5 Covariates

We include commonly observed predictors of an individual's subjective well-being in our regression analysis (see Dolan *et al.* (2008) for a review of this literature). These include individual-, household- and neighbourhood- level factors. Specifically, at the individual level we use age, higher education, relationship status, having a long-standing health condition, labour force status and commuting time. At the household level we use income, living with children, residence type (only available in the BHPS) and household space. At the neighbourhood level we include deprivation indices and air pollution, specifically annual ambient outdoor nitrogen dioxide (NO_2). A wave variable was included to account for any natural temporal progression in the data or anything specifically related to delivery of the instrument that year. Table 3.3 provides a description of each variable and Table 3.4 details the descriptive statistics for each variable in the total dataset for Greater London, and also that pertaining to the estimation samples for each model. We can see that each model is very similar to the overall BHPS and UKHLS samples.

It is likely that the relationship between well-being and open spaces is affected by socio-economic factors pertaining to neighbourhoods. Therefore, we include the English Indices of Multiple Deprivation. These are calculated by the Department for Communities and Local Government (p LSOAs and are based on 37 separate indicators, organised across seven distinct domains of deprivation (Department for Communities and Local Government 2010). In this analysis we include the Income Deprivation domain and the Employment deprivation domain, which measure the proportion of the population experiencing deprivation relating to low income and benefit claiming respectively. We also include the Crime Deprivation domain which reflects the risk of personal and material victimisation, and the Education Deprivation domain which relates to school performance and higher education rates.

It is also possible that air pollution levels affect the relationship between open spaces and well-being (Laffan 2018; Yuan *et al.* 2018). Here we include annual ambient outdoor NO_2 levels from the UK's Department for Environment, Food and Rural Affairs (Defra) as pollution-climate modelled values (Defra 2016). These are outputs based on dispersion modelling using point sources of known emission levels (e.g. monitoring stations, power stations, roadsides) and UK meteorological data, and are available as 1km x 1km grids for the UK as the annual mean NO_2 in $\mu g/m^3$. Each LSOA was given the pollution value of the nearest NO_2 point to each LSOA population-weighted centroid (obtained from the Office for National

Statistics geography portal). The pollution values were then attributed to every individual residing in each LSOA using the corresponding LSOA, BHPS individuals assigned 2008 values of NO_2, and UKHLS individuals assigned 2014 NO_2 values.

3.3.6 Analytic approach

We calculated the percentage area of each PPG17 category and subcategory for every London LSOA. This was then linked to every individual in the BHPS and UKHLS for each wave by the LSOA code of residence. We then linked the additional neighbourhood-level control variables (NO_2 and deprivation) in the same way. Missing data across all variables can be found in the BHPS and UKHLS and is due to wave nonresponse, item nonresponse, and respondent attrition. Where possible and appropriate we have imputed missing values from adjacent waves.

We take advantage of the panel nature of both of our surveys and use fixed effects regression. Fixed effects have a significant advantage over cross-sectional correlations as it allows us to isolate within-person variation as opposed to between-person variation. We effectively follow the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits), that could be related with both proximity to open space and subjective well-being.

The fixed effects regression was constructed as follows:

$$WB_{ijt} = \beta_0 + \beta_1 Q_{jt} + \beta_2 L_{jt} + \beta_3 X_{it} + \beta_4 T_t + \varepsilon_{ijt}$$

Where WB is the dependent variable (life satisfaction, GHQ or general health) for an individual i, at a given location j and in a given year t. It is a function of the PPG17 category/subcategory (Q_{jt}), a vector of LSOA neighbourhood factors (L_{jt}) and individuals' socio-economic and demographic characteristics (X_{it}), and a wave variable (T_t). ε_{ijt} is the error term (all remaining unaccounted for variation). All analysis was carried out using ArcGIS v10.6 (ESRI 2018) and regression analysis using the regress and xt suites in Stata 16 software (StataCorp 2019).

We constructed six model specifications in this analysis, and ran them for All Opens Space Sites, each PPG17 category and each subcategory (

Table 3.2). We also run these six models with additional subsets of the open space sites dataset: all open space sites, all green and bluespaces, all green only spaces, and all blue only spaces.

Table 3.2. The six model specifications used in this study, and run for each PPG17 category, subcategory and additional open space subset.

Model	Individual data	Well-being metric	Covariates
1	BHPS	Life satisfaction	+ all individual, household and neighbourhood level covariates
2		Mental health (GHQ)	
3		General health	
4	UKHLS	Life satisfaction	
5		Mental health (GHQ)	
6		General health	

Table 3.3. Variable descriptions (see alternative tables for PPG17 category and subcategory descriptions).

Variable name	Variable description
Life satisfaction	Respondent's self-reported life satisfaction (scale 1 to 7)
GHQ	Respondent's self-reported General Health Questionnaire score (scale 0 to 36)
General health	Respondent's self-reported general health (scale 1 to 5)
Spatial control variables	
Income deprivation	Indices of Multiple Deprivation – deprivation relating to low income and social benefit in the LSOA
Employment deprivation	Indices of Multiple Deprivation – deprivation relating to benefit claimant's in the LSOA
Education deprivation	Indices of Multiple Deprivation – deprivation relating to school performance and higher education rates in the LSOA
Crime deprivation	Indices of Multiple Deprivation – deprivation relating to the risk of personal and material victimisation in the LSOA
NO_2	Mean annual ambient nitrogen dioxide (NO_2) in respondent's residential LSOA ($\mu g/m^3$)
Age (yrs)	
16-25	Respondent's age is between 16-25 years (yes/no)
26-35	Respondent's age is between 26-35 years (yes/no)
36-45	Respondent's age is between 36-45 years (yes/no)
46-55	Respondent's age is between 46-55 years (yes/no)
56-65	Respondent's age is between 56-65 years (yes/no)
66-75	Respondent's age is between 66-75 years (yes/no)
75+	Respondent's age is 75+ years (yes/no)
University-level qualification	Respondent has a university-level qualification (yes/no)
In a relationship	Respondent is married or living as a couple (yes/no)
Living with children	Living with own children (<16yrs old)
Annual household income	Log equivalent annual household income (income divided by square root of household size (number of people))
Health condition	BHPS: Respondent self-reports a health condition that limits the type of work or amount of work they can do (yes/no) UKHLS: Respondent self-reports a long-standing physical or mental impairment, illness or disability (yes/no)
Employment status	
Employed	Respondent is employed (yes/no)
Unemployed	Respondent is unemployed or disabled (yes/no)
Retired	Respondent is retired (yes/no)
Caring for family	Respondent is caring for family (yes/no)
In training	Respondent is in training (yes/no)
House type (in BHPS only)	
Detached	Respondent lives in a detached house (yes/no)

Variable name	Variable description
Semi-detached	Respondent lives in a semi-detached house (yes/no)
Terraced	Respondent lives in a terraced house (yes/no)
Flat	Respondent lives in a flat (yes/no)
Other	Respondent lives in another type of dwelling e.g. bedsit (yes/no)
Household space	
< 1 room per person	Less than 1 room per person in the house (yes/no)
1 to < 3 rooms per person	Between 1 and under 3 rooms per person in the house (yes/no)
3 ≥ rooms per person	Three or more rooms per person in the house (yes/no)
Commuting time	
None	Respondent has no commute (yes/no)
≤ 15 mins	Respondent has a commute of 15 minutes or less (yes/no)
16-30 mins	Respondent has a 16-30 minute commute (yes/no)
31-50 mins	Respondent has a 31-50 minute commute (yes/no)
>50 mins	Respondent has a commute of over 50 minutes (yes/no)
Other	
Wave	BHPS wave (1-18) and UKHLS wave (1-8)

Table 3.4. Descriptive statistics of all variables used in both the BHPS and UKHLS analyses.

	All BHPS		All UKHLS	
Variable name	N	Mean (St.Dev.)	N	Mean (St.Dev.)
Life satisfaction	9,138	5.15 (1.25)	35,268	M=5.05 (1.51)
GHQ	14,301	11.18 (5.41)	36,735	M=10.98 (5.66)
General health	14,710	3.86 (0.93)	47,958	3.49 (1.11)
PPG17 subsets				
All open spaces	15,682	21.33 (21.64)	49,810	19.71 (19.66)
All green/bluespaces	15,682	21.04 (21.45)	49,810	19.41 (19.38)
All green spaces	15,682	20.44 (21.24)	49,810	17.72 (18.37)
All bluespaces	15,682	0.60 (3.25)	49,810	1.70 (6.77)
Number of PP spaces	15,682	3.65 (2.97)	49,810	3.20 (2.46)
PPG17 categories				
Allotments, Community Gardens and City Farms	15,682	1.01 (2.82)	49,810	0.68 (2.39)
Amenity	15,682	4.11 (9.05)	49,810	3.95 (7.96)
Cemeteries & Churchyards	15,682	0.86 (4.81)	49,810	0.94 (4.72)
Provision for Children & Teenagers	15,682	0.06 (0.43)	49,810	0.08 (0.52)
Civic Spaces	15,682	0.01 (0.24)	49,810	0.06 (0.60)
Green Corridors	15,682	2.22 (4.31)	49,810	3.06 (6.65)
Natural & Semi-Natural Urban Green space	15,682	2.33 (9.25)	49,810	1.84 (7.50)
Other	15,682	0.74 (3.69)	49,810	0.87 (4.19)
Other Urban Fringe	15,682	2.31 (9.64)	49,810	0.80 (5.48)
Outdoor Sports Facilities	15,682	3.98 (8.85)	49,810	2.85 (7.46)
Parks & Gardens	15,682	3.72 (9.77)	49,810	4.58 (10.58)
PPG17 Primary Use				
Adventure playground	15,682	0.00 (0.05)	49,810	0.01 (0.21)
Agriculture	15,682	2.21 (9.46)	49,810	0.70 (5.23)
Allotments	15,682	0.99 (2.81)	49,810	0.63 (2.33)
Amenity green space	15,682	0.42 (2.08)	49,810	0.44 (2.06)

	All BHPS		All UKHLS	
Variable name	N	Mean (St.Dev.)	N	Mean (St.Dev.)
Canal	15,682	0.06 (0.71)	49,810	0.25 (1.49)
Cemetery/churchyard	15,682	0.86 (4.81)	49,810	0.94 (4.72)
City farm	15,682	0.00 (0.06)	49,810	0.03 (0.46)
Civic/market square	15,682	0.01 (0.13)	49,810	0.02 (0.27)
Common	15,682	0.59 (4.78)	49,810	0.55 (4.61)
Community garden	15,682	0.02 (0.24)	49,810	0.02 (0.23)
Country park	15,682	0.67 (5.96)	49,810	0.16 (2.31)
Disused quarry/gravel pit	15,682	0.02 (0.43)	49,810	0.01(0.40)
Disused railway/trackbed	15,682	0.01 (0.16)	49,810	0.01 (0.14)
Educational	15,682	1.58 (3.97)	49,810	1.31 (3.63)
Equestrian centre	15,682	0.09 (0.99)	49,810	0.07 (1.10)
Formal garden	15,682	0.22 (1.29)	49,810	0.22 (1.10)
Golf course	15,682	0.54 (3.08)	49,810	0.45 (3.41)
Hospital	15,682	0.23 (2.11)	49,810	0.17 (2.37)
Land reclamation	15,682	0.06 (1.28)	49,810	0.32 (0.89)
Landscaping around premises	15,682	1.85 (7.73)	49,810	1.74 (5.64)
Nature reserve	15,682	0.85 (3.92)	49,810	0.86 (4.52)
Nursery/horticulture	15,682	0.01 (0.15)	49,810	0.03 (0.47)
Other	15,682	0.14 (0.78)	49,810	0.24 (2.68)
Other hard surfaced areas	15,682	0.01 (0.20)	49,810	0.04 (0.54)
Other recreational	15,682	0.32 (2.10)	49,810	0.21 (1.49)
Park	15,682	3.50 (9.69)	49,810	4.35 (10.53)
Play space	15,682	0.06 (0.42)	49,810	0.06 (0.46)
Playing fields	15,682	2.16 (7.08)	49,810	1.32 (5.18)
Private woodland	15,682	0.09 (0.66)	49,810	0.03 (0.38)
Public woodland	15,682	0.13 (1.27)	49,810	0.24 (2.32)
Railway cutting	15,682	0.87 (2.25)	49,810	0.81 (2.76)
Railway embankment	15,682	0.49 (1.62)	49,810	0.51 (1.78)
Recreation ground	15,682	1.07 (4.26)	49,810	0.85 (3.68)
Reservoir	15,682	0.01 (0.15)	49,810	0.28 (3.21)
River	15,682	0.53 (3.09)	49,810	1.17 (5.49)

	All BHPS		All UKHLS	
Variable name	N	Mean (St.Dev.)	N	Mean (St.Dev.)
Road island/verge	15,682	.021 (0.80)	49,810	0.22 (0.91)
Sewage/water works	15,682	0.20 (2.81)	49,810	0.17 (2.19)
Vacant land	15,682	0.33 (1.78)	49,810	0.42 (2.18)
Village green	15,682	0.18 (0.26)	49,810	0.02 (0.40)
Walking/cycling route	15,682	0.04 (0.38)	49,810	0.09 (0.67)
Youth area	15,682	0.00 (0.06)	49,810	0.01 (0.14)
Spatial control variables				
Income deprivation	15,682	0.17 (0.10)	49,810	0.23 (0.13)
Employment deprivation	15,682	0.09 (0.04)	49,810	0.18 (0.05)
Education deprivation	15,682	13.77 (10.74)	49,810	16.11 (10.52)
Crime deprivation	15,682	0.35 (0.59)	49,810	0.50 (0.56)
NO_2	15,682	28.73 (5.90)	49,810	29.44 (7.08)
Age (yrs)		Mean (St.Dev.) or %		Mean (St.Dev.) or %
16-25	15,682	17.71%	49,785	18.66%
26-35	15,682	21.56%	49,785	19.24%
36-45	15,682	18.24%	49,785	21.10%
46-55	15,682	16.21%	49,785	17.82%
56-65	15,682	12.00%	49,785	11.20%
66-75	15,682	7.93%	49,785	7.57%
75+	15,682	6.34%	49,785	4.41%
University-level qualification	15,682	26.72%	49,810	53.00%
In a relationship	15,682	58.01%	49,810	55.38%
Living with children	15,682	24.00%	49,810	31.95%
Annual household income	15,176	7.18 (0.84)	49,455	7.394 (0.69)
Health condition	15,610	16.22%	49,651	25.87%
Employment status				
Employed	15,613	61.34%	49,744	54.91%
Unemployed	15,613	7.06%	49,744	11.07%
Retired	15,613	16.17%	49,744	13.49%
Caring for family	15,613	7.92%	49,744	9.09%
In training	15,613	6.95%	49,744	10.76%

	All BHPS		All UKHLS	
Variable name	N	Mean (St.Dev.)	N	Mean (St.Dev.)
Other	15,613	0.56%	49,744	0.68%
House type				
Detached	15,030	6.81%	-	-
Semi-detached	15,030	25.40%	-	-
Terraced	15,030	34.88%	-	-
Flat	15,030	30.88%	-	-
Other	15,030	2.02%	-	-
Household space				
< 1 room per person	15,275	7.55%	49,538	19.24%
1 - < 3 rooms per person	15,275	77.55%	49,538	68.98%
3 $\geq$ rooms per person	15,275	14.90%	49,538	11.78%
Commuting time				
None	14,427	41.77%	44,626	49.54%
$\leq$ 15 mins	14,427	16.05%	44,626	10.61%
16-30 mins	14,427	16.75%	44,626	14.33%
31-50 mins	14,427	12.41%	44,626	12.38%
>50 mins	14,427	13.01%	44,626	13.14%

3.4 Results

We provide regression results for the PPG17 categories (unstandardised coefficients in Table 3.5 and standardised coefficients in Table 3.6) and PPG17 subcategories (unstandardised coefficients in Table 3.7 and standardised in Table 3.8), and full regression results for our models using the 'All Open Spaces' category only as the PPG17 dependent variable (see Table 3.9 for unstandardised coefficients and Table 3.10 for standardised coefficients). For the life satisfaction and self-reported general health models, a positive coefficient indicates that higher levels of open space coverage are related to better well-being. A negative coefficient in the GHQ regression analysis indicates that higher levels of open space coverage are related to better mental health level, the GHQ is inversely scored, so the higher the GHQ score the worse the individual reports their mental health.

Table 3.5. Unstandardised regression results for PPG17 categories with life satisfaction, GHQ and general health, showing results using the BHPS and the UKHLS data.

	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All open spaces	0.001 (0.001)	-0.004 (0.005)	0.001 (0.001)	0.000 (0.001)	0.002 (0.004)	0.001 (0.001)
PPG17 category	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Allotments, Community Gardens and City Farms	0.013 (0.009)	**-0.090**** **(0.034)**	-0.001 (0.005)	0.002 (0.011)	0.005 (0.035)	0.006 (0.005)
Amenity	0.001 (0.003)	-0.001 (0.011)	-0.001 (0.002)	0.006 (0.003)	0.009 (0.011)	0.000 (0.002)
Cemeteries & Churchyards	-0.005 (0.005)	-0.014 (0.020)	0.002 (0.003)	-0.010 (0.005)	-0.006 (0.018)	0.002 (0.003)
Provision for Children & Teenagers	0.005 (0.038)	-0.109 (0.162)	-0.010 (0.026)	-0.014 (0.042)	0.023 (0.139)	-0.011 (0.021)
Civic Spaces	0.165 (0.161)	0.513 (0.529)	0.103 (0.084)	-0.058 (0.038)	0.032 (0.129)	-0.006 (0.020)
Green Corridors	0.008 (0.005)	**-0.043*** **(0.018)**	0.001 (0.003)	0.001 (0.003)	0.014 (0.011)	**0.003*** **(0.002)**
Natural & Semi-natural Urban Green Space	**-0.007*** **(0.003)**	0.016 (0.011)	-0.001 (0.002)	-0.002 (0.003)	0.018 (0.010)	0.001 (0.002)
Other	0.004 (0.005)	-0.020 (0.018)	**0.010***** **(0.003)**	**0.020**** **(0.006)**	-0.023 (0.022)	0.003 (0.003)
Other Urban Fringe	0.004 (0.004)	-0.017 (0.014)	0.001 (0.002)	-0.005 (0.005)	-0.011 (0.016)	**-0.005*** **(0.003)**

	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Outdoor Sports Facilities	0.005 (0.003)	-0.014 (0.010)	0.000 (0.002)	0.004 (0.003)	**-0.029**** **(0.010)**	0.000 (0.001)
Parks & Gardens	0.000 (0.002)	0.016 (0.009)	0.001 (0.001)	-0.003 (0.003)	0.013 (0.008)	0.000 (0.001)
Observations	8,551	13,721	13,166	34,646	36,028	42,198
Individuals	1,614	2,165	2,185	10,795	11,349	12,655
R^2	0.04	0.03	0.13	0.05	0.07	0.21

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6. Standardised regression results for PPG17 categories with life satisfaction, GHQ and general health, showing results using the BHPS and the UKHLS data.

	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All Open Spaces	0.019	-0.017	0.022	0.006	0.009	0.013
PPG17 category	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Allotments, Community Gardens & City Farms	0.029	**-0.047****	-0.003	0.003	0.002	0.013
Amenity	0.006	-0.001	-0.011	0.029	0.013	0.001
Cemeteries & Churchyards	-0.020	-0.013	0.010	-0.031	-0.005	0.008
Provision for Children & Teenagers	0.002	-0.009	-0.005	-0.005	0.002	-0.005
Civic Spaces	0.031	0.022	0.025	-0.020	0.003	-0.003
Green Corridors	0.028	**-0.033***	0.003	0.006	0.017	**0.020***
Natural & Semi-natural Urban Green Space	**-0.057***	0.029	-0.006	-0.008	0.025	0.006
Other	0.013	-0.014	**0.041*****	**0.057****	-0.018	0.013
Other Urban Fringe	0.028	-0.029	0.014	-0.018	-0.011	**-0.026***
Outdoor Sports Facilities	0.037	-0.023	0.005	0.019	**-0.039****	0.002
Parks & Gardens	0.003	0.029	0.009	-0.024	0.024	0.001

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7. Unstandardised regression results for PPG17 subcategories with life satisfaction, GHQ and general health, showing results using the BHPS and the UKHLS data.

PPG17 primary purpose category	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Adventure playground	**-0.470*** **(0.221)**	0.785 (0.824)	0.119 (0.125)	-0.086 (0.075)	0.071 (0.256)	-0.045 (0.038)
Agriculture	0.004 (0.004)	-0.012 (0.014)	0.001 (0.002)	-0.005 (0.005)	-0.016 (0.017)	**-0.006*** **(0.003)**
Allotments	0.012 (0.009)	**-0.079*** **(0.035)**	-0.002 (0.006)	-0.001 (0.011)	-0.011 (0.037)	0.002 (0.006)
Amenity green space	0.019 (0.016)	-0.006 (0.058)	**-0.022*** **(0.009)**	0.020 (0.017)	-0.014 (0.057)	-0.001 (0.008)
Canal	0.015 (0.036)	0.112 (0.128)	0.020 (0.020)	**0.029*** **(0.014)**	**-0.126*** **(0.049)**	0.008 (0.007)
Cemetery/churchyard	-0.005 (0.005)	-0.014 (0.020)	0.002 (0.003)	-0.010 (0.005)	-0.006 (0.018)	0.002 (0.003)
City farm	-0.599 (0.760)	0.419 (1.124)	-0.071 (0.173)	0.047 (0.041)	0.116 (0.142)	**0.064**** **(0.020)**
Civic/market square	0.032 (0.225)	1.057 (0.680)	0.047 (0.104)	-0.021 (0.064)	**-0.446*** **(0.220)**	0.008 (0.035)
Common	-0.001 (0.004)	0.007 (0.015)	-0.004 (0.002)	-0.006 (0.005)	**0.054***** **(0.016)**	0.003 (0.002)
Community garden	0.050 (0.060)	**-0.647**** **(0.235)**	0.064 (0.038)	-0.038 (0.095)	**0.625*** **(0.307)**	0.012 (0.044)

Country park	**-0.017*** **(0.008)**	**0.068*** **(0.031)**	-0.000 (0.005)	-0.009 (0.009)	0.020 (0.032)	-0.000 (0.004)
Disused quarry/gravel pit	**-0.135*** **(0.054)**	0.400 (0.211)	0.014 (0.033)	-0.035 (0.033)	**0.241*** **(0.112)**	-0.034 (0.018)
Disused railway/trackbed	-0.372 (0.256)	**2.278*** **(0.990)**	-0.263 (0.154)	0.224 (0.147)	0.301 (0.527)	-0.070 (0.074)
Educational	0.001 (0.006)	0.017 (0.023)	**0.009*** **(0.003)**	-0.011 (0.006)	0.004 (0.021)	0.003 (0.003)
Equestrian centre	0.016 (0.022)	**-0.256**** **(0.094)**	0.009 (0.015)	-0.005 (0.014)	0.031 (0.048)	0.002 (0.008)
Formal garden	0.043 (0.023)	0.016 (0.074)	0.019 (0.011)	**-0.053*** **(0.021)**	0.085 (0.071)	-0.009 (0.010)
Golf course	**0.023*** **(0.009)**	**-0.063*** **(0.030)**	0.003 (0.005)	-0.006 (0.006)	**-0.047*** **(0.020)**	-0.001 (0.003)
Hospital	-0.010 (0.009)	0.014 (0.037)	-0.002 (0.007)	0.006 (0.020)	0.128 (0.066)	-0.002 (0.010)
Land reclamation	-0.017 (0.028)	0.016 (0.051)	**0.017*** **(0.008)**	**0.051*** **(0.025)**	0.031 (0.087)	-0.025 (0.014)
Landscaping around premises	0.001 (0.004)	-0.007 (0.013)	-0.003 (0.002)	0.007 (0.005)	0.027 (0.015)	0.000 (0.002)
Nature reserve	**-0.013*** **(0.006)**	0.020 (0.022)	0.005 (0.003)	0.004 (0.005)	-0.010 (0.016)	-0.001 (0.002)

Nursery/horticulture	-0.145 (0.143)	-0.039 (0.447)	0.047 (0.069)	-0.143 (0.121)	-0.368 (0.413)	0.015 (0.064)
Other	**0.078*** **(0.035)**	-0.190 (0.108)	0.026 (0.017)	**0.033**** **(0.011)**	-0.065 (0.039)	0.002 (0.005)
Other hard surfaced areas	0.295 (0.226)	-0.317 (0.834)	0.197 (0.138)	-0.072 (0.046)	0.269 (0.158)	-0.010 (0.025)
Other recreational	0.007 (0.006)	0.024 (0.025)	-0.002 (0.004)	0.002 (0.010)	-0.052 (0.035)	0.001 (0.005)
Park	-0.000 (0.002)	0.016 (0.009)	0.001 (0.001)	-0.003 (0.003)	0.012 (0.008)	0.000 (0.001)
Play space	0.023 (0.040)	-0.169 (0.167)	-0.019 (0.026)	0.030 (0.053)	-0.015 (0.176)	0.006 (0.027)
Playing fields	0.003 (0.005)	-0.018 (0.015)	-0.002 (0.002)	**0.014**** **(0.005)**	-0.028 (0.016)	0.001 (0.002)
Private woodland	-0.122 (0.091)	0.509 (0.365)	0.038 (0.059)	0.039 (0.062)	-0.029 (0.207)	-0.005 (0.034)
Public woodland	-0.006 (0.013)	-0.046 (0.053)	0.002 (0.008)	0.003 (0.016)	-0.042 (0.053)	0.001 (0.009)
Railway cutting	0.002 (0.012)	**-0.086*** **(0.038)**	0.001 (0.006)	0.003 (0.009)	0.011 (0.029)	0.001 (0.004)
Railway embankment	0.021 (0.014)	0.004 (0.051)	0.004 (0.008)	**0.028*** **(0.013)**	-0.004 (0.043)	-0.003 (0.007)

Recreation ground	0.001 (0.006)	-0.009 (0.019)	0.005 (0.003)	-0.001 (0.005)	-0.017 (0.017)	0.000 (0.003)
Reservoir	0.203 (0.111)	-0.777 (0.482)	**0.150* (0.074)**	**0.021** (0.007)**	-0.037 (0.024)	-0.004 (0.004)
River	0.005 (0.007)	**-0.053* (0.024)**	0.001 (0.004)	-0.002 (0.004)	0.022 (0.013)	**0.005* (0.002)**
Road island/verge	0.025 (0.026)	0.118 (0.092)	-0.018 (0.014)	-0.044 (0.025)	**0.206* (0.087)**	**-0.027* (0.013)**
Sewage/water works	0.007 (0.006)	-0.023 (0.023)	**0.011** (0.004)**	0.001 (0.015)	0.028 (0.052)	0.007 (0.008)
Vacant land	-0.008 (0.015)	-0.024 (0.043)	0.002 (0.007)	0.016 (0.010)	-0.040 (0.032)	0.009 (0.005)
Village green	0.026 (0.079)	-0.076 (0.317)	0.072 (0.052)	**-1.824* (0.879)**	-4.396 (2.999)	0.404 (0.488)
Walking/cycling route	0.011 (0.048)	0.069 (0.197)	-0.009 (0.030)	-0.026 (0.034)	-0.038 (0.113)	0.013 (0.018)
Youth area	-0.051 (0.193)	0.507 (0.849)	0.153 (0.170)	-0.502 (0.536)	0.299 (1.826)	-0.241 (0.268)
PPG17 subset	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All green/blue open spaces	0.001 (0.001)	-0.004 (0.005)	0.000 (0.001)	0.000 (0.001)	0.002 (0.004)	0.001 (0.001)

All green open spaces	0.001 (0.001)	-0.002 (0.005)	0.000 (0.001)	-0.000 (0.001)	0.002 (0.005)	0.000 (0.001)
All blue open spaces	0.006 (0.007)	**-0.049*** **(0.023)**	0.002 (0.003)	0.004 (0.003)	0.003 (0.011)	0.003 (0.002)
Number of PPG PP categories	0.010 (0.010)	-0.037 (0.034)	0.006 (0.005)	0.001 (0.010)	-0.039 (0.035)	0.006 (0.005)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8. Standardised regression results for PPG17 subcategories with life satisfaction, GHQ and general health, showing results using the BHPS and the UKHLS data.

PPG17 primary purpose category	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Adventure playground	**-0.022***	0.008	0.007	-0.011	0.003	-0.008
Agriculture	0.027	-0.021	0.012	-0.017	-0.015	**-0.030***
Allotments	0.027	**-0.041***	-0.007	-0.001	-0.005	0.003
Amenity green space	0.032	-0.002	**-0.051***	0.028	-0.005	-0.002
Canal	0.011	0.015	0.016	**0.028***	**-0.033***	0.010
Cemetery/churchyard	-0.020	-0.013	0.010	-0.031	-0.005	0.008
City farm	-0.027	0.004	-0.004	0.014	0.009	**0.025****
Civic/market square	0.003	0.020	0.005	-0.004	**-0.020***	0.002
Common	-0.005	0.007	-0.019	-0.018	**0.043*****	0.011
Community garden	0.012	**-0.030****	0.017	-0.006	**0.024***	0.003
Country park	**-0.086***	**0.078***	-0.002	-0.014	0.009	-0.000
Disused quarry/gravel pit	**-0.051***	0.034	0.006	-0.011	**0.020***	-0.013
Disused railway/trackbed	-0.053	**0.072***	-0.048	0.016	0.006	-0.009
Educational	0.004	0.012	**0.039***	-0.027	0.003	0.009
Equestrian centre	0.010	**-0.047****	0.010	-0.004	0.006	0.002
Formal garden	0.043	0.004	0.025	**-0.038***	0.017	-0.009
Golf course	**0.061***	**-0.036***	0.011	-0.014	**-0.029***	-0.002
Hospital	-0.017	0.005	-0.003	0.009	0.054	-0.005
Land reclamation	-0.021	0.004	**0.024***	**0.033***	0.005	-0.020
Landscaping around premises	0.007	-0.010	-0.028	0.024	0.026	0.001
Nature reserve	**-0.046***	0.015	0.020	0.012	-0.008	-0.003
Nursery/horticulture	-0.015	-0.001	0.006	-0.042	-0.030	0.007
Other	**0.047***	-0.025	0.022	**0.062****	-0.032	0.004
Other hard surfaced areas	0.048	-0.012	0.041	-0.022	0.022	-0.005
Other recreational	0.012	0.009	-0.004	0.002	-0.014	0.001
Park	-0.001	0.029	0.006	-0.018	0.022	0.003
Play space	0.008	-0.013	-0.009	0.009	-0.001	0.002
Playing fields	0.017	-0.023	-0.014	**0.052****	-0.027	0.004
Private woodland	-0.064	0.060	0.026	0.010	-0.002	-0.002

Public woodland	-0.007	-0.011	0.003	0.005	-0.019	0.002
Railway cutting	0.004	**-0.036***	0.002	0.006	0.005	0.003
Railway embankment	0.027	0.001	0.007	**0.034***	-0.001	-0.004
Recreation ground	0.003	-0.007	0.022	-0.003	-0.011	0.000
Reservoir	0.029	-0.022	**0.026***	**0.046****	-0.022	-0.011
River	0.014	**-0.029***	0.003	-0.007	0.022	**0.022***
Road island/verge	0.017	0.017	-0.016	-0.028	**0.034***	**-0.023***
Sewage/water works	0.015	-0.012	**0.033****	0.002	0.012	0.014
Vacant land	-0.011	-0.008	0.003	0.022	-0.015	0.017
Village green	0.005	-0.003	0.017	**-0.485***	-0.306	0.157
Walking/cycling route	0.005	-0.003	-0.004	-0.011	-0.004	0.008
Youth area	-0.003	0.005	0.006	-0.047	0.007	-0.031
PPG17 subset	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All green/blue open spaces	0.016	-0.015	0.009	0.006	0.006	0.014
All green open spaces	0.012	-0.007	0.007	-0.003	0.005	0.006
All blue open spaces	0.018	**-0.028***	0.006	0.020	0.003	0.018
Number of PPG PP categories	0.022	-0.020	0.020	0.001	-0.017	0.014

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9. Full unstandardised regression results with All Open Spaces.

Variable name	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All open spaces	0.001	-0.004	0.001	0.000	0.002	0.001
	(0.001)	(0.005)	(0.001)	(0.001)	(0.004)	(0.001)
Spatial control variables						
Income deprivation	-0.675	**-6.172***	**-1.418*****	-0.269	-1.664	-0.318
	(0.716)	**(2.609)**	**(0.409)**	(0.605)	(2.038)	(0.300)
Employment deprivation	2.341	9.338	**2.328****	0.474	2.128	0.497
	(1.326)	(4.785)	**(0.746)**	(1.247)	(4.204)	(0.618)
Education deprivation	-0.006	**0.030***	0.001	-0.002	0.011	-0.001
	(0.004)	**(0.014)**	(0.002)	(0.004)	(0.013)	(0.002)
Crime deprivation	-0.072	0.020	0.017	0.061	**0.350***	0.040
	(0.059)	(0.201)	(0.031)	(0.051)	**(0.173)**	(0.026)
NO_2	-0.006	0.026	-0.002	0.000	0.006	-0.001
	(0.007)	(0.024)	(0.004)	(0.005)	(0.016)	(0.002)
Age (yrs) (reference category: 46-55)						
16-25	**-0.348****	0.449	**-0.201****	-0.058	0.143	-0.098
	(0.122)	(0.438)	**(0.068)**	(0.100)	(0.337)	(0.050)
26-35	**-0.303*****	**0.657***	-0.088	-0.027	0.222	-0.040
	(0.091)	**(0.326)**	(0.051)	(0.073)	(0.245)	(0.037)
36-45	**-0.197****	**0.478***	0.000	-0.041	0.014	-0.013
	(0.061)	**(0.214)**	(0.033)	(0.047)	(0.161)	(0.024)
56-65	**0.151***	**-0.969*****	0.036	0.111	**-0.540****	-0.030
	(0.062)	**(0.221)**	(0.035)	(0.057)	**(0.193)**	(0.029)
66-75	0.169	-0.828*	-0.011	**0.233***	**-0.863****	0.018
	(0.107)	(0.378)	(0.059)	**(0.092)**	**(0.310)**	(0.046)
75+	0.038	-0.446	-0.100	0.244	-0.612	-0.045
	(0.147)	(0.527)	(0.081)	(0.131)	(0.444)	(0.066)
University-level qualification	**-0.225***	0.216	-0.008	-0.099	0.154	-0.025

	(0.114)	(0.345)	(0.054)	(0.072)	(0.243)	(0.037)
In a relationship	**0.250*****	**-0.517****	0.037	0.083	-0.130	-0.019
	(0.051)	**(0.179)**	(0.028)	(0.048)	(0.160)	(0.024)
Living with children	-0.062	-0.138	0.003	-0.032	0.014	-0.021
	(0.051)	(0.177)	(0.028)	(0.043)	(0.145)	(0.022)
Annual household income	-0.010	0.008	**-0.034****	**0.041***	**-0.162****	-0.005
	(0.019)	(0.073)	**(0.012)**	**(0.018)**	**(0.060)**	(0.009)
Health condition	**-0.398*****	**1.965*****	**-0.579*****	**-0.153*****	**0.885*****	**-0.333*****
	(0.043)	**(0.152)**	**(0.023)**	**(0.025)**	**(0.084)**	**(0.013)**
Employment status (reference category: employed)						
Unemployed	**-0.309*****	**1.006*****	**-0.125****	**-0.281*****	**1.657*****	**-0.070****
	(0.070)	**(0.248)**	**(0.039)**	**(0.046)**	**(0.154)**	**(0.023)**
Retired	0.102	**-0.563***	-0.010	0.140*	-0.335	0.051
	(0.075)	**(0.273)**	(0.043)	(0.065)	(0.219)	(0.032)
Caring for family	0.075	0.163	-0.069	0.050	**0.338***	-0.018
	(0.070)	(0.253)	(0.040)	(0.051)	**(0.171)**	(0.025)
In training	-0.027	-0.199	**-0.108***	0.075	0.270	0.007
	(0.082)	(0.284)	**(0.045)**	(0.055)	(0.185)	(0.027)
Other	**-0.365***	0.211	-0.122	-0.048	0.419	0.008
	(0.149)	(0.626)	(0.099)	(0.105)	(0.356)	(0.053)
House type (reference category: detached)						
Semi-detached	**-0.152***	-0.147	0.008	-	-	-
	(0.076)	(0.276)	(0.043)			
Terraced	-0.091	-0.230	0.001	-	-	-
	(0.082)	(0.293)	(0.046)			
Flat	-0.083	0.012	-0.015	-	-	-
	(0.086)	(0.314)	(0.049)			
Other	**-0.316***	0.495	-0.018	-	-	-
	(0.130)	(0.477)	(0.075)			
Household space (reference category: 1 - < 3 rooms						

per person)						
< 1 room per person	-0.092	**0.598****	-0.037	0.061	-0.130	-0.022
	(0.064)	**(0.223)**	(0.035)	(0.043)	(0.146)	(0.021)
3 $\geq$ rooms per person	0.021	**-0.474****	0.051	0.000	0.192	**-0.055***
	(0.052)	**(0.184)**	(0.029)	(0.049)	(0.164)	**(0.025)**
Commuting time (reference category: no commute)						
$\leq$ 15 mins	0.030	-0.200	0.000	-0.018	**-0.284***	0.038
	(0.058)	(0.209)	(0.033)	(0.043)	**(0.144)**	(0.022)
16-30 mins	0.082	**-0.461***	-0.004	-0.042	-0.035	0.016
	(0.057)	**(0.208)**	(0.033)	(0.039)	(0.132)	(0.020)
31-50 mins	0.084	-0.398	-0.001	-0.036	-0.027	0.005
	(0.061)	(0.222)	(0.035)	(0.041)	(0.138)	(0.021)
>50 mins	0.068	-0.091	-0.041	-0.041	0.053	0.003
	(0.061)	(0.224)	(0.035)	(0.041)	(0.137)	(0.021)
Wave	**-0.015****	**0.067*****	**-0.020*****	0.007	0.003	**-0.026*****
	(0.005)	**(0.016)**	**(0.003)**	(0.005)	(0.016)	**(0.002)**
Constant	**5.698*****	**9.873*****	**4.470*****	**4.620*****	**11.375*****	**4.281*****
	(0.275)	(0.937)	(0.148)	(0.234)	(0.787)	(0.117)
Observations	8,551	13,721	13,166	34646	36028	42,198
Individuals	1,614	2,165	2,185	10,795	11,349	12,655
R^2	0.04	0.03	0.13	0.05	0.07	0.21

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10. Full standardised regression results with All Open Spaces.

Variable name	BHPS			US		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All open spaces	0.019	-0.017	0.022	0.006	0.009	0.012
Spatial control variables						
Income deprivation	-0.054	**-0.113***	**-0.152*****	-0.022	-0.036	-0.036
Employment deprivation	0.082	0.076	**0.112****	0.015	0.019	0.023
Education deprivation	-0.047	**0.059***	0.016	-0.012	0.020	-0.012
Crime deprivation	-0.034	0.002	0.011	0.023	**0.035***	0.020
NO_2	-0.026	0.029	-0.014	0.002	0.008	-0.009
Age (yrs) (reference category: 46-55)						
16-25	**-0.102****	0.031	**-0.082****	-0.015	0.010	-0.034
26-35	**-0.097*****	**0.050***	-0.039	-0.007	0.015	-0.014
36-45	**-0.061****	**0.034***	0.000	-0.011	0.001	-0.005
56-65	**0.041***	**-0.059*****	0.013	0.024	**-0.030****	-0.009
66-75	0.038	**-0.042***	-0.003	**0.042***	**-0.041****	0.004
75+	0.007	-0.019	-0.026	0.032	-0.021	-0.008
University-level qualification	**-0.083***	0.018	-0.004	-0.033	0.014	-0.011
In a relationship	**0.098*****	**-0.047****	0.020	0.027	-0.011	-0.008
Living with children	-0.021	-0.011	0.001	-0.010	0.001	-0.009
Annual household income	-0.007	0.001	**-0.030****	**0.018***	**-0.020****	-0.003
Health condition	**-0.116*****	**0.134*****	**-0.231*****	**-0.045*****	**0.069*****	**-0.133*****
Employment status (reference category: employed)						
Unemployed	**-0.060*****	**0.048*****	**-0.034****	**-0.056*****	**0.088*****	**-0.020****
Retired	0.031	**-0.038***	-0.004	**0.032***	-0.020	0.016
Caring for family	0.015	0.008	-0.020	0.009	**0.016***	-0.005
In training	-0.005	-0.009	**-0.030***	0.015	0.015	0.002
Other	**-0.022***	0.003	-0.009	-0.003	0.006	0.001
House type						

(reference category: detached)						
Semi-detached	**-0.053***	-0.012	0.004	-	-	-
Terraced	-0.035	-0.020	0.001	-	-	-
Flat	-0.030	0.001	-0.007	-	-	-
Other	**-0.031***	0.010	-0.002	-	-	-
Household space (reference category: 1 - < 3 rooms per person)						
< 1 room per person	-0.018	**0.029****	-0.010	0.015	-0.008	-0.008
3 ≥ rooms per person	0.006	**-0.032****	0.020	0.000	0.011	**-0.017***
Commuting time (reference category: no commute)						
≤ 15 mins	0.009	-0.014	0.000	-0.004	**-0.016***	0.011
16-30 mins	0.024	**-0.032***	-0.002	-0.010	-0.002	0.005
31-50 mins	0.022	-0.024	-0.000	-0.008	-0.002	0.002
>50 mins	0.019	-0.006	-0.015	-0.009	0.003	0.001
Wave	**-0.047****	**0.062*****	**-0.112*****	0.011	0.001	**-0.055*****
Constant	-	-	-	-	-	-

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.1 Which PPG17 categories are important for subjective well-being?

Using the BHPS, we find a positive relationship between well-being and Allotments, community gardens and city farms, Green corridors, and Other, and a negative relationship with Natural and semi-natural urban green space. Allotments, community gardens and city farms are positively associated with mental health (b=-0.090, β=-0.047, p=0.009), Green corridors are positively related to mental health (b=-0.043, β=-0.033, p=0.021) and 'Other' is positively related to general health (b=0.010, β=0.041, p<0.001). Natural and semi-natural urban green space is negatively associated with life satisfaction in the BHPS (b=-0.007, β=-0.057, p=0.019).

Using the UKHLS, we find a positive relationship between well-being and Green corridors, Other, and Outdoor sports facilities, and a negative relationship with Urban fringe. Green corridors are positively related to general health (b=0.003, β=0.020, p=0.038), Other is positively related to life satisfaction (b=0.020, β=0.057, p=0.002), and Outdoor sports facilities are positively related to mental health (b=-0.029, β=-0.039, p=0.002). Urban fringe is negatively related to general health (b=-0.005, β=-0.026, p=0.038).

There are two PPG17 categories where we find a significant relationship with well-being in both the BHPS and the UKHLS (although in different well-being measures; Figure 3.4). Green corridors and Other are both positively related with well-being in both surveys. Green corridors are positively related to mental health in the BHPS and general health in the UKHLS. Other is positively related to general health in the BHPS and life satisfaction in the UKHLS. We do not find any significant relationships with any well-being measure in either survey with Amenity green space, Cemeteries & churchyards, Provision for children & teenagers, Civic spaces, and Park & gardens.

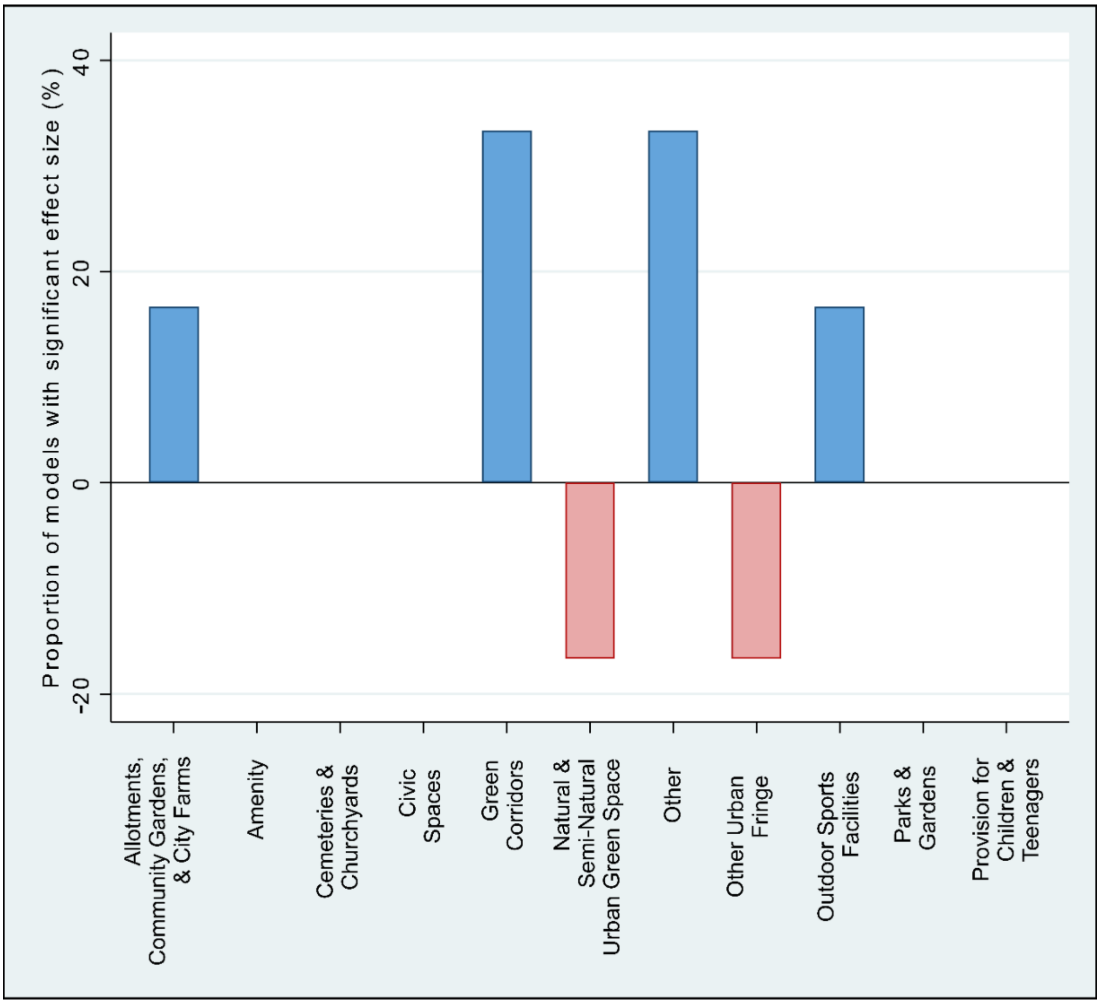

Figure 3.4. The percentage of models which included significant effect sizes for different open space categories.

The unstandardized coefficients (b) represent the change in subjective well-being (on the scale specific to life satisfaction, GHQ, or general health) due to a 1% increase in open space category in the LSOA. For example, a 1% increase in Green corridor coverage in an LSOA is associated with a 0.043 point improvement in mental health as measured on the GHQ scale of 0-36. However, if we use standardised coefficients we can compare effect sizes within and across models. Standardised coefficients (β) relate to the 1 standard deviation change in subjective well-being due to a 1 standard deviation increase in open space coverage in the LSOA. The magnitude of the effect sizes of the significant PPG17 categories range from β=0.020 to 0.057, with Other having a positive effect size twice the size that of Green corridors, and Natural and semi-natural urban green space having a negative effect size twice that of Other urban fringe.

Across the significant standardised results, we find the categories with the largest positive median effect sizes are Other and Allotments, Community Gardens and City Farms (Figure 3.5). The category with the largest negative median effect size is Natural and semi-natural urban green space.

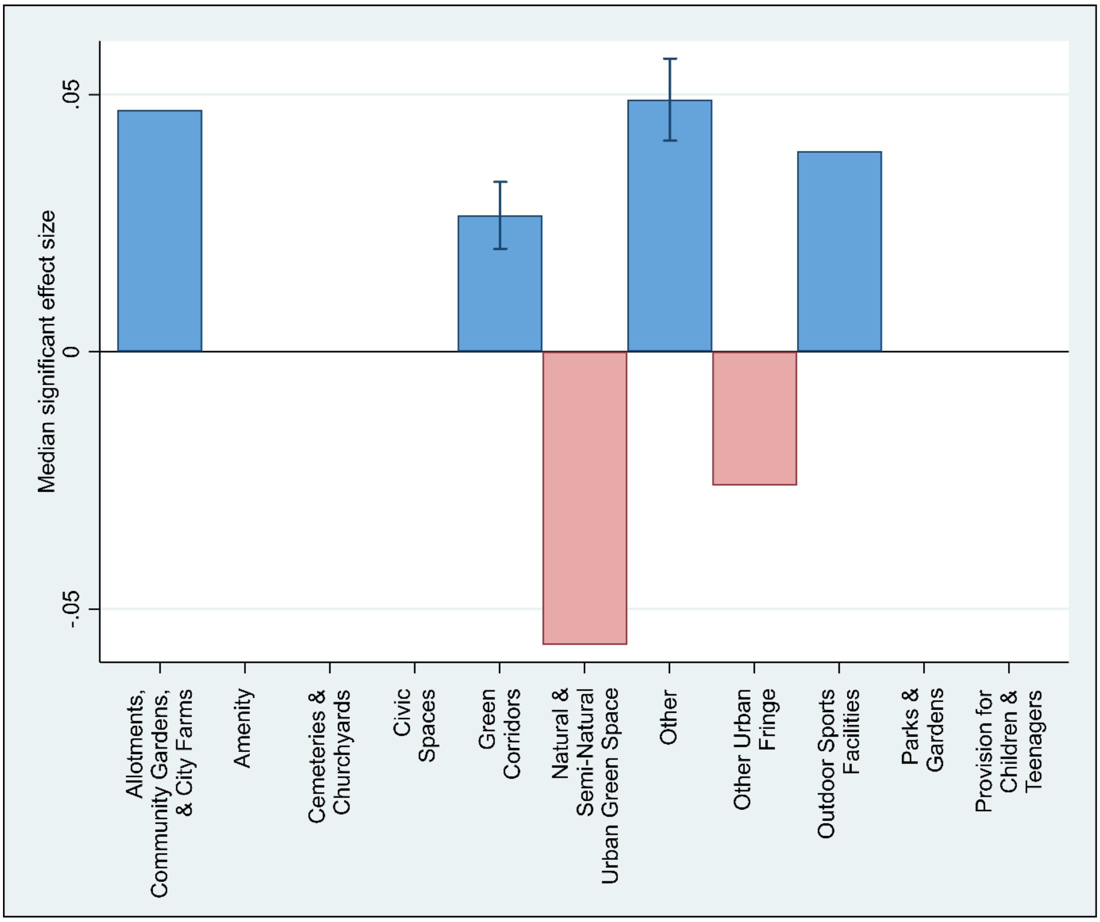

Figure 3.5. The median standardised effect size across the significant coefficients for each model specification under each PPG17 category, showing error bars where more than one model was found to have a significant coefficient.

3.4.2 Which PPG17 subcategories are important for subjective well-being?

Using the BHPS, we find a positive significant relationship between well-being and Allotments, Community gardens, Golf courses, Other, Land reclamation, Railway cuttings, Reservoirs, Rivers, and Sewage/water works. We find significant negative associations with Adventure playgrounds, Amenity greenspace, Country parks, Disused quarry/gravel pit, and Nature reserves.

In the BHPS, we find positive associations between life satisfaction and Golf courses (b=0.023, β=0.061, p=0.011) and Other (b=0.078, β=0.047, p=0.026), and negative associations between life satisfaction and Adventure playgrounds (b=-0.470, β=-0.022, p=0.033), Country parks (b=-0.017, β=-0.086, p=0.043; b=0.068), Disused quarry/gravel pit (b=-0.135, β=-0.051, p=0.012), and Nature reserves (b=-0.013, β=-0.046, p=0.021). We find positive associations between mental health and Allotments (b=-0.079, β=-0.041, p=0.024), Community gardens (b=-0.647, β=-0.030, p=0.006), Equestrian centres (b=-0.256, β=-0.047, p=0.007), Golf courses (b=-0.063, β=-0.036, p=0.036), Railway cuttings (b=-0.086, β=-0.036, p=0.025), and Rivers (b=-0.053, β=-0.029, p=0.027), and negative associations with Country parks (b=0.068, β=0.078, p=0.026) and Disused railway/trackbeds (b=2.267, β= 0.071, p=0.021). We find positive associations between self-reported general health and Land reclamation (b=0.017, β=0.024, p=0.032), Reservoirs (b=0.150, β=0.026, p=0.043), and Sewage/water works (b=0.011, β=0.033, p=0.003), and negative associations with Amenity green space (b=-0.022, β=-0.051, p=0.012).

Using the UKHLS, we find positive relationships between well-being and Canals, City farms, Civic/market square, Golf courses, Land reclamation, Other, Playing fields, Railway embankments and Reservoirs, and Rivers. We find negative relationships between well-being and Agriculture, Commons, Community gardens, Formal gardens, and Village greens.

Using the UKHLS we find significant positive associations between life satisfaction and Canals (b=0.029, β=0.028, p=0.040), Land reclamation (b=0.051, β=0.033, p=0.044), Other (b=0.033, β=0.062, p=0.004)l, Playing fields (b=0.014, β=0.052, p=0.003), Railway embankments (b=0.028, β=0.034, p=0.033), and Reservoirs (b=0.021, β=0.046, p=0.002), and negative associations with Formal gardens (b=-0.053, β=-0.038, p=0.011) and Village greens (b=-1.824, β=-0.485, p=0.038). We find significant positive associations between mental health and Canals (b=-0.126, β=-0.033, p=0.010), Civic/market square (b=-0.446, β=-0.020, p=0.042), and Golf courses (b=-0.047, β=-0.029, p=0.019), and negative associations with Commons (b=0.054, β=0.043, p=0.001), Community gardens (b=0.625, β=0.024, p=0.042), and Road verges (b=0.206, β=0.034, p=0.018). We find significant positive associations between self-reported general health and City farms (b=0.064, β=0.025, p=0.002), and Rivers (b=0.005, β=0.022, p=0.017), and negative associations with Agriculture (b=-0.006, β=-0.030, p=0.020) and Road islands/verges (b=-0.027, β=-0.023, p=0.040).

We do not find any significant relationships with any well-being measure in either survey with Cemetery/churchyards, Educational, Hospital, Landscaping around premises, Nursery/horticulture, Other hard surfaced areas, Other recreational, Park, Play space, Private woodland, Public woodland, Recreation ground, Vacant land, Walking/cycling route, and Youth area.

There are two PPG17 subcategories where we find a significant relationship with well-being in both the BHPS and the UKHLS with the same well-being measure: Golf courses and Other (Figure 3.6). Golf courses are significantly and positively associated with life satisfaction and mental health in the BHPS, and with mental health in the UKHLS. Golf courses is the only category to have significant results in two well-being measures in the same survey, as well as the same well-being measure in both surveys. The 'Other' category is positively related to life satisfaction in the both the BHPS and the UKHLS.

As well as Golf courses, we find one other PPG17 subcategory that has a significant association with two measures of well-being in the same survey. Canals is positively associated with life satisfaction and mental health in the UKHLS. We also find other subcategories that have positive relationships in both surveys, although they are with different well-being measures. Land reclamation is positively associated with general health in the BHPS and positively with life satisfaction in the UKHLS. Reservoirs are positively associated with general health in the BHPS and life satisfaction in the UKHLS. Rivers are positively related to mental health in the BHPS and general health in the UKHLS.

We find one PPG17 subcategory that has negative associations in both surveys (albeit with different well-being measures). Disused quarry/gravel pit is negatively related to life satisfaction in the BHPS and with mental health in the UKHLS. We also find two PPG17 subcategory that have a negative association with two well-being measures in the same survey. Road island/verges are negatively associated with mental health and general health in the UKHLS. Country parks are negatively associated with life satisfaction and mental health in the BHPS.

We find one PPG17 subcategory with a positive relationship with a well-being measure in the BHPS but a negative relationship with the same well-being measure in the UKHLS.

Community gardens are positively related to mental health in the BHPS but negatively related to mental health in the UKHLS.

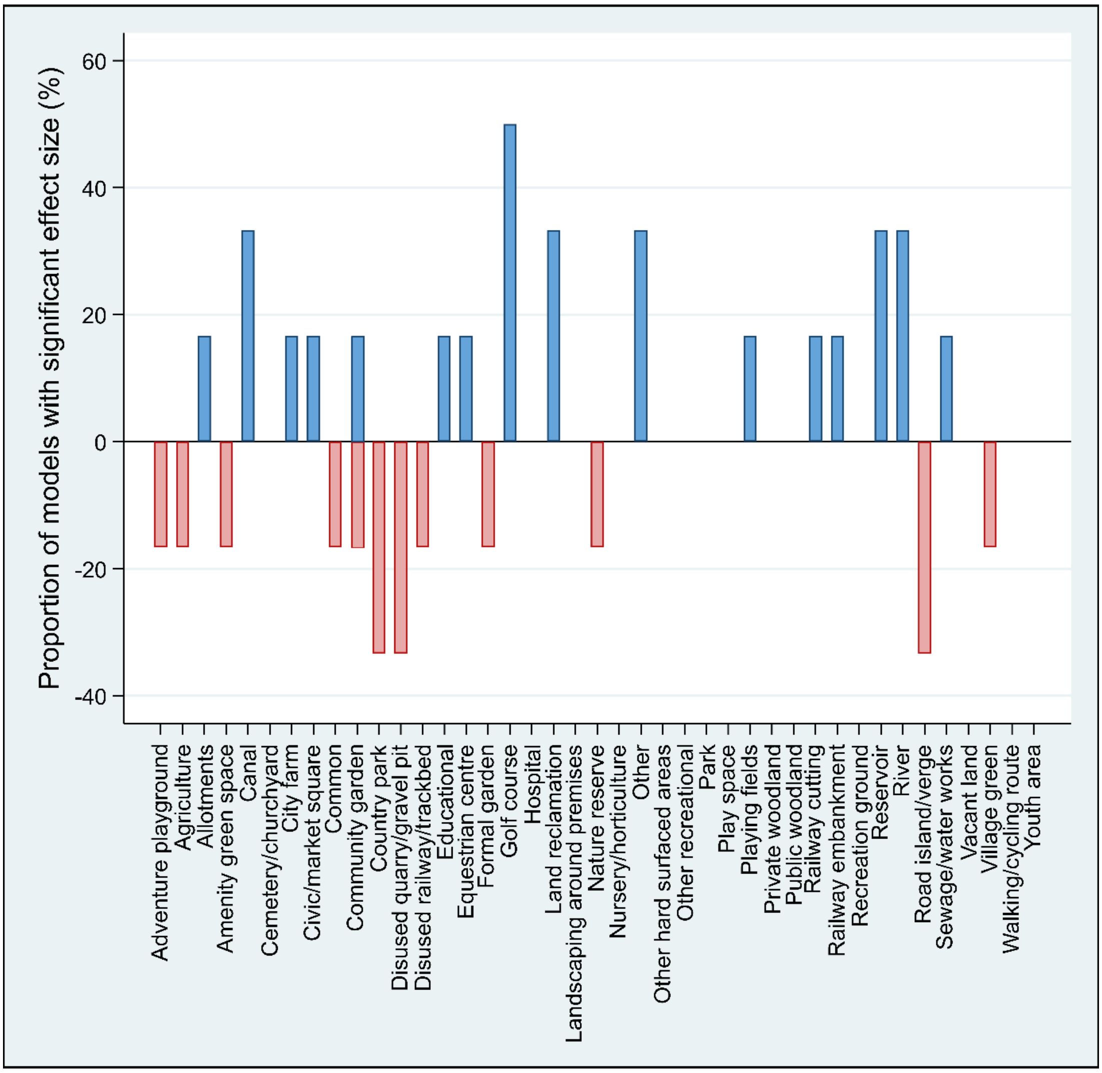

Figure 3.6. The percentage of models which included significant effect sizes for different open space subcategories.

Again, the unstandardized coefficients (b) represent the change in subjective well-being (on the scale specific to life satisfaction, GHQ, or general health) due to a 1% increase in open space subcategory in the LSOA. Standardised coefficients (β) relate to the 1 standard deviation change in subjective well-being due to a 1 standard deviation increase in open space subcategory coverage in the LSOA. The effect sizes all range between β =0.020 and 0.086 (positive or negative), with one exception for village greens (β=-0.485), which must be treated with caution given the small number of village green spaces within the Greater London area. The effects of the different open space subcategories on subjective well-being are therefore comparable with each other.

Across the significant results, we find the categories with the largest positive median effect sizes are Other, Playing fields, Equestrian centres, Allotments and Golf courses (Figure 3.7). The subcategories with the largest negative median effect sizes are Village green, Country parks, disused railway/trackbed, amenity green space, and nature reserve.

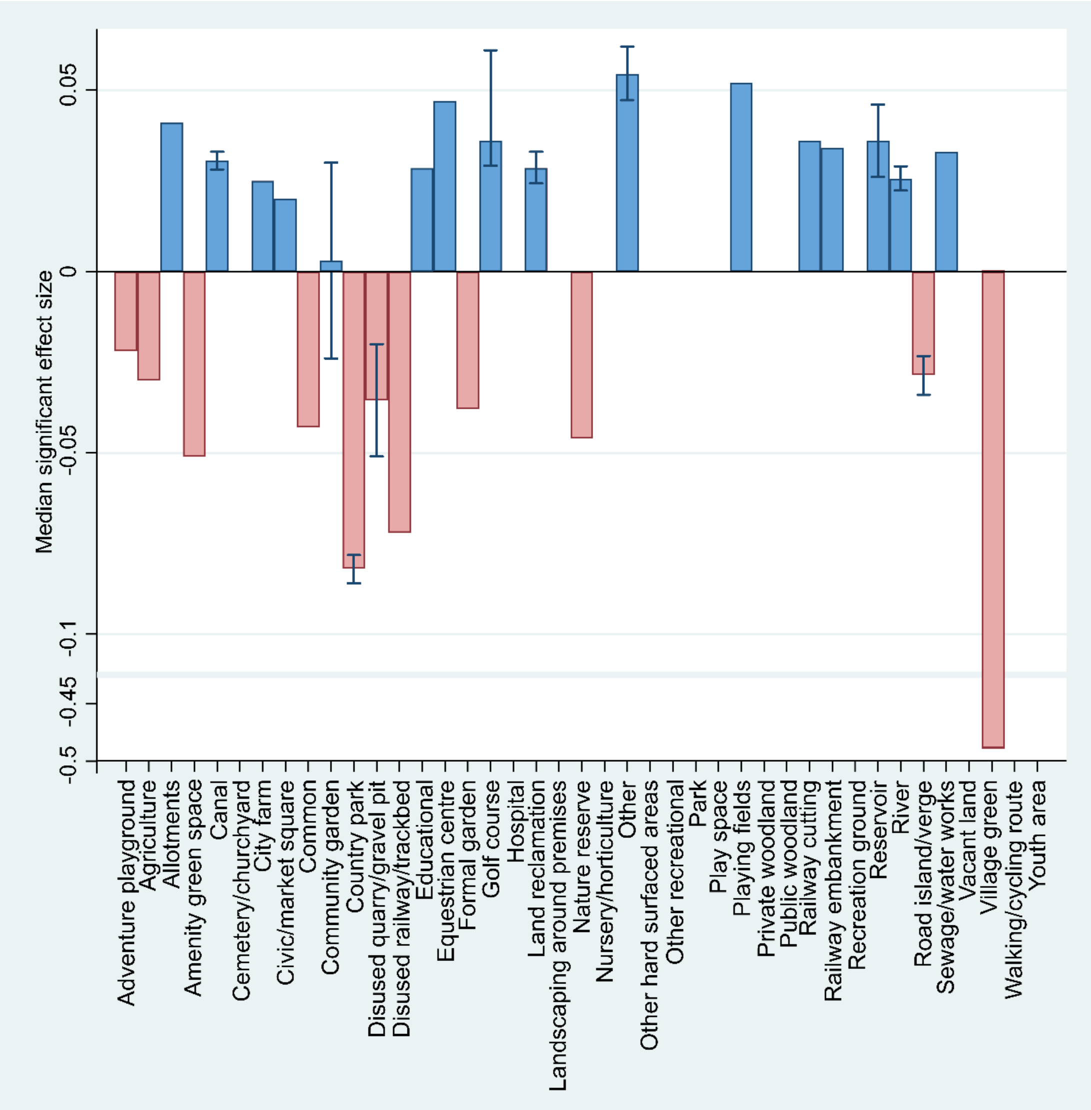

Figure 3.7. The median standardised effect size across the significant coefficients for each model specification under each PPG17 category.

3.4.3 Open space sites subsets and subjective well-being

We do not find a significant relationship between the category 'all open spaces' and any of our three measures of well-being. This is true for both the BHPS and the UKHLS. We also do not find a significant relationship for 'all green and bluespaces' or 'all green spaces only' with any of our three subjective well-being measure, in either survey. We do however find a significant and positive relationship between the GHQ and 'all bluespaces only' in the BHPS (b=-0.049, β=-0.028 p=0.037).

3.4.4 What are the relationships between subjective well-being and individual- and neighbourhood-level covariates?

We find being unemployed (e.g. life satisfaction BHPS: b=-0.309, β=-0.060, p<0.001; UKHLS: b=-0.281, β=-0.056, p<0.001) and having a health condition (e.g. life satisfaction BHPS: b=-0.398, β=-0.116, p<0.001; UKHLS b=-0.153, β=-0.045, p<0.001) are significant negative determinants of all three well-being measures across both surveys. Having a health condition has the largest effect sizes across all our models, and has larger effect sizes in the BHPS than in the UKHLS. We also find lower levels of life satisfaction and poorer mental health associated with younger age categories when compared to the 46-55 category, and higher levels of life satisfaction and improved mental health in higher age brackets when compared to the 46-55 category. This relationship is stronger in the BHPS than in the UKHLS. Interestingly, we find that being in a relationship is beneficial for life satisfaction and mental health in the BHPS only, with no significant results in the UKHLS models. Conversely, we find annual household income a significant determinant of life satisfaction and mental health in the UKHLS but not in the BHPS, where we find it is negatively related to general health.

3.5 Discussion

Despite much research indicating clear well-being benefits of the natural environment, there are also several studies that do not find any relationship. These mixed findings may result from the aggregated definition of green- and bluespaces used in the study, or the analytical methods used. In this study, when using the new aggregated categories, we did not find any association between any well-being measures and total green spaces or total green and bluespaces, however we do find a relationship between mental health and total bluespace in the BHPS. These findings suggest that the aggregation of greenspaces is not useful, similarly with combining green- and bluespaces together. They highlight that identifying water bodies in a typology is a good step, with further disaggregation required across open space categories to account for the heterogeneous nature of open spaces. This supports similar findings in another recent study (Jarvis *et al.* 2020b).

In this study, we address these issues by using an existing land use typology to disaggregate open spaces, and also employ two large longitudinal panel datasets, allowing us to examine within-person variation in the relationship between natural spaces and subjective well-being. We find several signals of relationships between the PPG17 typology and three different subjective well-being measures across the two panel surveys. We find positive relationships between well-being and bluespaces, and with land use types relating to recreation or community use, such as golf courses and allotments. We also find several land uses with significant negative relationships with well-being, which is less commonly reported in the literature.

Using standardised coefficients allows us to compare effect sizes with other known determinants of well-being in the models. For example, the positive effect of Allotments, community gardens and city farms, and Green corridors on mental health in the BHPS are similar in size to that of the negative effect of being unemployed when compared to being employed ($\beta=0.048$, $p<0.001$), and approximately a third of the effect size of having a health condition ($\beta=0.134$, $p<0.001$). The positive effect of outdoor sports facilities on mental health in the UKHLS is half the negative effect size of being unemployed when compared to being employed ($\beta=0.088$, $p<0.001$) and having a health condition ($\beta=0.069$, $p<0.001$). When we look at the standardised coefficients (β) in our subcategory analysis, again we find the effect sizes to be comparable to that of other important explanatory variables. For example, the positive effects of Golf courses on life satisfaction in the BHPS are similar to the negative effect of being unemployed when compared to being employed (β=-0.060, $p<0.001$), and approximately half the negative effect size of having a health condition (β=-0.116, $p<0.001$). The positive effect of canals on life satisfaction in the UKHLS is approximately half of the negative effect size of being unemployed when compared to being employed (β=-0.055, $p<0.001$) and half that of having a health condition (β=-0.045, $p<0.001$).

The use of a disaggregated categorisation of green- and bluespaces clearly highlights the heterogeneous effects of different components of natural open spaces. Of the 41 PPG17 subcategories, we found 37% were positively associated with well-being, 37% had no association with well-being, and 26% were negatively associated with well-being. Our study demonstrates the importance of accounting for type when assessing the well-being benefits of the natural environment, as this may provide more insight into which land uses are more beneficial than others.

3.5.1 Are there open space categories and subcategories that are particularly beneficial or deleterious for the well-being of residents?

Positive relationships between well-being and land use

In terms of median effect sizes, the subcategories with the greatest well-being benefits are Other, Playing fields, Equestrian centres, Allotments and Golf courses. These open spaces tend to be large areas of green or blue open space, associated with recreation or physical activities. They are also likely to be associated with a sense of community, for example team sports, members clubs and shared facilities. This supports current literature which suggests that green and blue open spaces provide well-being benefits by providing opportunities for physical activity, by building social cohesion, and positive feelings of purpose (Nieuwenhuijsen *et al.* 2017; van den Berg *et al.* 2010b). It is likely that many of these sites have restricted or private, or semi-private (e.g. fee-paying) access only. Whether the well-being benefits associated with living near to these land uses are achieved by residents directly accessing and using these sites, likely with allotments, or by some other means, we cannot say. For example, golf and horse-riding are relatively specialist interests and do not appeal to the broader community, and playing fields are likely to be used by sports clubs or schools. Certainly, evidence suggests that neighbourhoods with large green and blue open spaces are related to increased house prices, lower population density, or by improving the broader natural environment i.e. cleaner air or higher biodiversity (Czembrowski &

Kronenberg 2016; Laffan 2018). It therefore becomes important here to consider causality of the relationship. For example, it could be that golf courses inflate local house prices, and therefore individuals that live near them are on average wealthier. Given that wealthier individuals, or those with a higher socioeconomic status, are more likely to report higher levels of subjective well-being, the relationship between proximity to golf courses and well-being might be due indirectly to selective residential sorting.

There are three specific 'blue' open space subcategories Canals, Rivers and Reservoirs, and these are all significantly and positively associated with two measures of well-being across the two surveys. This finding suggests that bluespaces are important for well-being, and that they provide unique benefits to green spaces. This distinction between green and bluespaces is important, and adds to the current literature that explores the effect of proximity to blue environments on human well-being (Finlay *et al.* 2015; Mavoa *et al.* 2019a; Nutsford *et al.* 2016; Triguero-Mas *et al.* 2015; White *et al.* 2013a). It is also important here to distinguish between the different types of bluespace. Each type is associated with a different combination of well-being measures and is therefore suggestive of different mechanisms by which well-being benefits are achieved. For example, they may differentially offer opportunities for physical activity, different aesthetical values, or, specific to London or any large city, associated facilities e.g. South Bank promenade.

Negative relationships between well-being and land use

We find several negative relationships between subjective well-being and open space categories and subcategories. Surprisingly some of the largest negative effect sizes are with land cover types associated with expected higher quality green space. The subcategories Village greens, Country parks, Amenity green space and Nature reserves all reflect urban greenspace sites that are likely to be maintained and managed for recreation and social purposes, but also for higher levels of biodiversity and cleanliness. This contradicts previous research that suggests cleaner and/or more biodiverse locations are associated with higher levels of well-being (Brindley *et al.* 2019; Wheeler *et al.* 2015). The context of these sites might be important here, particularly in London. Many of London's newest nature reserves are built on abandoned industrial land, such as Gillespie Park and Railway Fields (Fields in Trust 2019), this may mean the surrounding area is perceived as relatively undesirable, or surrounded by a residential community with lower socioeconomic status and therefore relatively more likely to report lower levels of well-being. To an extent, we attempt to control for these factors by including the Indices of Multiple Deprivation, but as this analysis was at the LSOA-level, it may mask some of the more localised components of this relationship.

This would suggest that the relationship between open spaces and well-being varies between people and places (Giles-Corti *et al.* 2008; Labib *et al.* 2020b). This was found by Houlden et al., (2019) who conducted a cross-sectional analysis of mental health and green space provision across London using Geographically Weighted Regression (GWR), a technique that allows model parameters to vary over space by accounting for statistically significant spatial clustering of model residuals. They found stronger positive associations between mental health and greenspace provision in the North, South and West of London, and less so in the East. They also found stronger positive associations nearer the edge boundary of London, with weaker and sometimes negative associations in central London.

No relationship

The absence of any relationship between well-being and both public and private woodland is also surprising and contradictory to previous research (Ward Thompson *et al.* 2013; Zhang & Tan 2019). However woodland in a city may be considered unsafe (Milligan & Bingley 2007a), although we do attempt to account for this by including the crime domain of the Indices of Multiple Deprivation. Without further information on the specific characteristics of woodland spaces, such as quality, safety, accessibility, it is difficult to explain this finding.

The lack of any significant relationships between well-being and the park and gardens category is surprising, and contrary to previous research (Wood *et al.* 2017). There are no significant associations with the park subcategory and only one with the formal garden subcategory, and that is a negative relationship (with life satisfaction in the UKHLS). Perhaps this may be explained by the diversity of features within the description of a park. An area defined as a park may or may not contain bluespaces, natural habitat including woodland, outdoor sports facilities and other recreational features such as cafes, and play spaces. Therefore, given the likely breadth of type of park within this subcategory, the relationship with well-being may well be difficult to interpret. Further analysis within this subcategory is needed, for example identifying the number of features and characteristics in each park.

Similarly, the absence of any relationship between well-being and the Amenity category was also surprising. This category by definition should provide a pleasant and appealing landscape. The subcategories (amenity green space, village green, hospital, educational, landscaping around premises, reservoir), again reflecting both green and bluespace, are intended to provide opportunities for aesthetic enjoyment, recreation and social activity in nature. However, this is only reflected in the educational and reservoir subcategories. Negative relationships are found with amenity greenspace and village greens. It is likely that any well-being benefits from the hospital subcategory are experienced by those using the hospital and not residents in that neighbourhood. Similarly, it is especially surprising to find no association with landscaping around premises, particularly as this will sometimes relate to open space surrounding residential developments.

Other additional surprising findings were that with the provision for children and teenagers. The absence of any significant relationship between well-being and the provision for children and teenagers is likely to be due to the surveys only including individuals aged 16 and over, or perhaps again pertaining to unmeasured characteristics of the spaces, such as quality, cleanliness, safety and naturalness.

3.5.2 Is the PPG17 typology useful for understanding how different components of open space contribute to well-being?

In this paper, we also wanted to find out if this existing open space land cover typology, used in planning regulation and guidance in the UK, is useful for understanding how open spaces might be delivering well-being benefits to residents. The PPG17 typology is widely used by English boroughs and councils to design and assess the open space provision in their area. To this end, it provides a consistent and easy to use tool that allows for comparisons across space and time. However, we find that several of the higher categories are too broad in their definition of open space. Either this is reflected by the inconsistent nature of the subcategories under each category e.g. bluespaces, or the heterogeneous nature of the sites categorised under each subcategory, e.g. Parks and gardens. Additionally, time series data is not available for this dataset, this would allow us to capture if changes in well-being through time is caused by changes in open space provision.

Bluespace

The PPG17 categorisation masks the positive well-being effects of the bluespace subcategories (Rivers, Canals and Reservoirs), which are distributed across different higher categories. The Green corridors category has a misleading name as it is actually comprised of both green and blue subcategories (River, Canal, Railway cutting, Railway embankment, Disused railway/trackbed, Road island/werge, and Walking/cycling paths). Although canals, and possibly certain sections of rivers, provide green corridors too (bankside/towpath vegetation), this categorisation does not fully capture specifically the bluespace element of these spaces. The Reservoirs subcategory is nested in the Amenity category, and is the only 'blue' subcategory in this group. Additionally and unfortunately, bluespace features that are nested within other open space subcategories, such as a lake in a park, will not be reflected in this typology. Given the current literature that explores the specific and distinct well-being benefits gained from bluespaces (Nutsford *et al.* 2016), the PPG17 categories cannot be used to make this distinction.

Other

The 'Other' category and subcategory were both associated with higher levels of wellbeing. This category is comprised of a range of land use types which makes it difficult to interpret. Indeed the subcategory 'other' suffers from the same issue. By searching the site names within this category, we can see land uses include: 9 car parks, 6 camping or caravan sites, 1 leisure centre, 17 gardens (square, peace, terrace etc), 7 ponds/lagoons, 2 zoos, 3 airfields/aerodromes, 1 quarry, 2 docks, 1 marina, 1 theatre, 1 construction site, and 1 tipping site. Many of these land uses incorporate green and bluespace, and are associated with recreation and leisure activities. This could explain why both the category and subcategory of Other are positively related to subjective well-being. This category and subcategory needs to be better defined to be able to understand the association with well-being.

Allotments, community gardens and city farms

The Allotments, community gardens and city farms category finds an overall positive relationship with mental health in only one survey, which perhaps reflects the same significant relationships found with the Allotments and Community gardens subcategories. However, this overall category masks the conflicting relationships found across the two surveys for community gardens, and also masks the positive relationship between city farms and general well-being in the UKHLS. It is intuitive to find a positive well-being association with allotments. This type of land use has previously been shown to improve health and well-being by encouraging interactions with nature, and increasing levels of social and physical activity. Older people in particular have been found to experience high levels of achievement, satisfaction and aesthetic pleasure from their allotment gardening (Milligan *et al.* 2004; van den Berg *et al.* 2010b). The same may be true for city farms too. The conflicting results for community gardens is unusual and may reflect changes in these gardens over time.

New open space categories

We find that several of the subcategories are found in very small numbers across the city e.g. youth areas and community gardens, and so this provides a robust rationale for aggregating subcategories to higher categories, in the case of spatial and statistical analysis. For example, it is plausible that the contradictory results that we find for communal gardens are due to the small coverage of this subcategory in the city. This is why we attempted to create new categories in the typology that may better reflect the characteristics of open spaces that are associated with higher levels of well-being.

3.5.3 Do the results differ between the three measures of well-being?

For the PPG17 categories, within each separate survey, we did not find a significant relationship with more than one measure of well-being for each open space category. For the PPG17 subcategories, within each separate survey, we find three subcategories with a relationship between more than one measures of well-being: Golf courses, Canals, and Road island/verges. Golf courses and Canals both find positive effects in life satisfaction and mental health, and Road island/verges have a negative relationship with mental health and general health.

These findings suggest that the three well-being measures are capturing different aspects of human well-being, and that some land use categories/subcategories have an effect on certain well-being measures and not others. This implies that any land use strategy designed for improving well-being should consider the complex pathways between how different types of open space differentially effect individuals through different well-being metrics.

3.5.4 Do the results differ between the two surveys?

For the PPG17 categories, we did not find the same well-being measure to be significant across both the BHPS and the UKHLS for the same open space category. For the subcategories, we find the same well-being measure to be significant across both surveys for two subcategories: Other and Golf courses. The Other subcategory has a positive relationship with life satisfaction in both surveys, and Golf courses with mental health. We find a significant association with Community gardens and mental health in both surveys but one is positive and the other is negative. We do not find any subcategories with a significant relationship with general health in both surveys.

This was surprising, but it suggests that there are important differences between the surveys in how individual well-being is related to aspects of the natural environment. Indeed this supports previous research that found a significant positive relationship between urban greenspace and well-being using the BHPS in England (White *et al.* 2013b), but found no relationship with the UKHLS (Houlden *et al.* 2017). Despite both surveys designed to be nationally representative, they have different sampling structures and spatial distributions across the city. Both surveys have a clustered and stratified sampling design in their main sample for England, but the BHPS participants are drawn from 250 primary sampling units, in contrast to over 3000 in the UKHLS. Therefore, the BHPS has a more clustered spatial distribution than the UKHLS. Respondent attrition is a common problem in panel surveys, and Lynn and Borkowska, (2018) found attrition rates in both the BHPS and UKHLS were greater amongst younger age groups, men, black people and participants on lower incomes. Moreover, they find the UKHLS main sample had a higher attrition rate than the BHPS. This might be important; several studies have highlighted the potential significance that individual characteristics play in the relationship between well-being and the natural environment. For example, the relationship between residential greenspace and mental distress was found to vary with age and gender in nine waves of the BHPS (Astell-Burt *et al.* 2014c). In another study, only those individuals in the lower socio-economic status category, as measured by education attainment, were found to have a significant association between well-being and surrounding greenspace (de Vries *et al.* 2003). Additionally, the >120minute physical activity threshold for achieving well-being benefits from neighbourhood greenspace was significant for the White British category but not for others, suggesting potential differences by ethnicity in relationships between natural spaces and health and well-being benefits in England (White *et al.* 2019). If those in younger age groups, men, black individuals and those with lower incomes are under-represented in both surveys, and more so in the UKHLS, it seems likely that this will contribute to different outcomes in the analyses.

The BHPS and UKHLS are also collected in different time periods, and may reflect how the relationship between individuals and the natural environment changes through time. Additionally the PPG17 dataset represents current open space provision, up-to-date as of December 2018, and temporal change data is not available. Therefore, this dataset is less likely to reflect the actual open space provision the further back in time we look. This is potentially a problem, particularly for the BHPS, which runs from 1991-2008.

3.5.5 Implications, limitations, and future work

Implications

The recent revisions of the PPG17 to the National Planning Policy Framework signal an exciting shift towards land use planning to enhance well-being through the provision of open space. It recommends future developments to "create places that are safe, inclusive and accessible and which promote health and well-being, with a high standard of amenity for existing and future users" (Department for Communities and Local Government 2019). However, despite the PPG17 land use typology being used nationally, to the best of our knowledge there has only been one other study that explores how the different types of open space in this typology are related to human well-being. So far there has been no revision or replacement of the PPG17 land use typology in the new framework, and there now is an important opportunity to reform and improve any future such systems. There is a clear need for a broader collaboration of specialisms in urban land use design, including ecologists, public health experts, social scientists and land use planners (Sandifer *et al.* 2015). Much work highlights the missing links between research, guidance and implementation (Crawford 2010), but other work studying greenspace provision in English cities demonstrated the 'dynamic and policy-responsive nature of urban land use' (Dallimer *et al.* 2011). The findings of this study can help to provide well-being research in a usable manner for integration into policy guidance for implementation at the local and regional level.

Strengths, limitations, and suggestions for future work

To the best of our knowledge, this is one of only two studies to use the PPG17 typology to assess the impacts of open space on subjective well-being. The other study, conducted by Houlden et al., (2019a), only used three of the higher categories to define open spaces in London. We used accurate, up-to-date and freely available open space data, as well as a suite of control variables. We have used two large panel surveys and three measures of subjective well-being, allowing us to compare two populations or survey instruments, as well as identify how the natural environment affects different aspects of an individual's health and well-being. Importantly, we have employed longitudinal fixed effects regression to better control for potential sources of endogeneity, which addresses a key limitation in much of the well-being and nature literature.

Whilst the PPG17 data provides a large and consistent land cover typology, as described above there are issues regarding the categorisation of land cover types. For example, the Parks and Gardens category covers such a broad spectrum of land cover types that it is difficult to capture specific features that may have a beneficial or deleterious effect on well-being. PPG17 categories do not allow for recognition of mixed use e.g. when a park contains a river/reservoir, and it would be very interesting to explore the effect these different features in parks have on individual well-being. For example, does a park that contains bluespace provide more well-being benefits than a park without bluespace? This cannot be carried out with the PPG17 typology as it is, and creating further subcategories would be problematic given the relatively small number of sites in some subcategories already. An interesting next step would be to aggregate the subcategories in a new set of higher categories based on a different set of open space characteristics that are more aligned with current understanding of the impacts on well-being.

We used longitudinal well-being data pertaining to two large samples in London, across two survey instruments. Using two surveys was useful to explore whether the relationships between open space and subjective well-being measures were found across different subsamples. However, the two surveys have some potentially important differences. First, the BHPS runs from 1991-2008 and the UKHLS data used in this analysis runs from 2009 to 2017. This difference in time period, and therefore factors affecting the population, might explain the differences found between the two surveys. Second, despite both surveys having robust sampling strategies to represent Greater London, they are different, and therefore they differ in size and geographic range. The latter could be important, as there may be less exposure to certain PPG17 categories/subcategories in different geographical locations. Future research could use spatially-explicit modelling techniques, such as Geographically-Weighted Regression, to examine how the relationship between well-being and natural spaces varies geographically. Third, the PPG17 data reflects the provision of open space in December 2018. In the absence of longitudinal PPG17 data, we are unable to reflect change through time. Until this becomes available, the lack of longitudinal open space data will always hinder such analysis.

We focussed the analysis on a specific area, Greater London, because the data was up-to-date, well maintained and freely available. Focussing on a sub-national level also allows us to use high-resolution spatial data, which is important when focussing on individual people.

Of course, this means that the survey data is not nationally representative. The relationships found will be specific to Greater London. Indeed looking at the well-being benefits of open spaces in a large city like London is particularly urgent, given the global trend for increasingly large urban populations.

We use the LSOA administrative boundary as the residential unit but of course there are alternative spatial units that could be applied, such as Euclidean or network buffer zones. Indeed limiting the analysis to LSOA boundaries does not allow us to address the modifiable area unit problem, in that we cannot test if we get similar or different results for different sized or shaped units (Pasanen *et al.* 2019). However, LSOAs in Greater London are smaller and more consistent in size than across the entire country, so in some senses this makes it a more robust unit. The PPG17 spatial data only applied to Greater London, therefore we have not been able to account for any open space that occurs outside of the city boundary, despite there being potential areas in close proximity to perimeter LSOAs. An important next step would be to conduct this analysis at the national level, but this is currently hindered by PPG17 data availability.

Our analysis used presence of open space sites in residential neighbourhoods, which of course does not imply that residents actually use the open spaces directly. Indeed the use of, rather than proximity to, green/bluespace may be better linked with well-being benefits (Triguero-Mas *et al.* 2017). However, it is reasonable to assume that nearby accessible open spaces are more likely to be visited; data for England for 2012/13 indicated that 66% of visits to the natural environment were within two miles of home (Natural England 2013). Furthermore, the well-being benefits associated with residential proximity to open spaces sites may be achieved indirectly by improving biodiversity, or providing views of green and bluespaces (Nutsford *et al.* 2016). Future work could incorporate access rights to explore the importance of distinguishing between private and public land, and certainly sub-LSOA analysis might suggest additional factors that cannot be incorporated in this study. Additionally, the PPG17 typology specifically excludes private, domestic gardens as it is a categorisation for public spaces only. However, there is some evidence demonstrating the well-being benefits related with access and use of domestic gardens (de Bell *et al.* 2020b; de Vries *et al.* 2003). Important future work could control for access to private open spaces, and examine how the characteristics of these spaces relate to well-being.

Land cover, or type of open space, appears to be an important metric for exploring the relationship between human well-being and open space. However, it does not necessarily capture the range of other characteristics about an open space that could potentially influence how, and if, well-being benefits are achieved by individuals. As mentioned previously, the quality of each site is not inherent to the categories or subcategories. Factors such as cleanliness and safety may be important, as well as ecological factors such as biodiversity. For example, Brindley et al., (2019) found that cleanliness of each PPG17 category impacted health of residents in Sheffield. Future work should include metrics relating to the quality of open spaces. The concept of ecosystem services might also offer new analytical and evaluation tools which can help to plan, develop and manage urban greenspace (Haaland & van den Bosch 2015; Kabisch 2015).

Conclusions

With the recent revision of the National Planning Policy Framework for England, there is an emphasis on land use planning to enhance well-being through the provision of open space. It specifically highlights the need for high quality public open spaces and local green and bluespace, as well as provision for recreation, sports and places that encourage social interaction, physical activity and the protection of biodiversity. Our findings suggest that there are differences in the well-being effects of the components of green- and bluespaces in London, and that specific land uses can be beneficial or deleterious for residential well-being. Bluespaces certainly appear to be important in our study and should be categorised separately in any future categorisation of urban open spaces.

Chapter 4: The association between the quality of public green and blue spaces and subjective well-being in London

4.1 Abstract

There is now considerable evidence that the natural environment provides health and well-being benefits in urban environments, however, evidence is varied, and often contradictory. One potential reason for this inconsistency is the quality of public green and blues spaces. Here we examine the impact of the quality of public natural spaces on subjective well-being, referring to their importance for nature conservation. We also explore the impact of private open spaces on well-being, and if this affects the relationship between public open spaces and well-being. We use the British Household Panel Survey (BHPS), a large, longitudinal panel dataset, to identify adults in London in 1991-2008. We use two Greenspace Information for Greater London (GiGL) areas of deficiency datasets; deficiency to Sites of Importance for Nature Conservation (SINCs) and deficiency to Public Open Spaces (POSs). SINCs are open spaces that have significant biodiversity importance, and we use biodiversity as a proxy for quality. Deficiency is calculated as living more than a 1km walk from a POS or SINC (calculated using actual travelling routes and known access points). We find that living within a 1km walk of a SINC in Greater London increases an individual's life satisfaction by 0.117 points on a scale of 1 to 7. There is no significant relationship between well-being and access to all POS. Therefore, we find that the *quality* of public green and blue spaces in London is important for the well-being of residents in London. We also find that access to private open space has a positive and significant relationship with well-being, which is separate to that with public open space. Therefore, both public and private green and blue spaces are important for well-being for residents in London.

4.2 Introduction

Natural environments have been shown to be important determinants of human health and well-being (Sandifer *et al.* 2015). Proximity and use of green and blue spaces have been associated with a range of benefits, such as higher levels of subjective well-being (Mavoa *et al.* 2019a; White *et al.* 2013b), improved self-esteem and 2mood (Barton & Pretty 2010), perceived good general health (Maas *et al.* 2006), psychological restoration (Wood *et al.* 2018), and lower levels of self-reported depression, anxiety and stress (Mennis *et al.* 2018). They have also been associated with lower levels of obesity (Pereira *et al.* 2013), cardiovascular disease (Pereira *et al.* 2012) and lower levels of all-cause mortality (Crouse *et al.* 2017; Mitchell & Popham 2008).

Exposure to the natural environment has been shown to be particularly important to those in urban environments (Cox *et al.* 2018). With two-thirds of the global human population estimated to be living in urban environments by 2050 (World Health Organisation 2016), cities are likely to densify, resulting in the loss of urban green and blue spaces. In fact, this is already occurring in cities across the world (Haaland & van den Bosch 2015). The potential for more people to become disconnected from the natural world is growing, labelled the 'extinction of experience' (Soga & Gaston 2016). Importantly therefore, the likelihood that people will not achieve the health and well-being benefits associated with natural spaces increases. Given that the biggest growth in the urban population will be in low- to middle-income households (WHO 2016), this presents a social equity issue, which could be addressed through evidence-based urban planning and green infrastructure design (Jennings *et al.* 2017).

How people are exposed to, experience and receive benefits from natural environments in urban settings is complex. Research has shown that access to natural spaces increases the likelihood that people will use them. Previous research also suggests that green/blue spaces surrounding an individual's residential location have an impact on their health and well-being. This might be because neighbourhood open spaces are nearby and therefore potentially more accessible, increasing the likelihood that individuals will gain well-being benefits from them. Many studies that examine this relationship show that higher levels of green and blue spaces close to an individual's residence are associated with higher levels of subjective well-being (Ambrey & Fleming 2013; Astell-Burt *et al.* 2014c; Maas *et al.* 2009a; Wheeler *et al.* 2015; White *et al.* 2013b). However, several studies have found there to be no such association (Bos *et al.* 2016; Houlden *et al.* 2017; Triguero-Mas *et al.* 2017). One possible explanation for the contrasting findings in the literature may be due to differences in the quality of the natural spaces not being accounted for. Certainly several studies have identified this as a gap in our understanding (Akpinar *et al.* 2016; Brindley *et al.* 2019). One potential reason why this has been relatively poorly researched is that quality itself is a broad term, often subjective in nature, and therefore one that can be measured in many ways. The Sustainable Development Goals (SDGs) aim for universal access to good quality and accessible green spaces in cities by 2030 (United Nations 2017). Therefore, it is not just the amount of green/blue space in urban areas that is important, but also the quality of these spaces. More research is needed to better understand if, and how, quality of green and blue spaces provides health and well-being benefits. Determining what metrics of quality are important for well-being is also an important research area.

Only a small handful of studies have attempted to capture quality characteristics of the natural environment when exploring how an individual receives well-being benefits from it. Francis et al., (2012) found that certain physical features of public open spaces in Perth, Australia, such as water features, birdlife and walking paths, have a strong relationship with good mental health. Brindley et al., (2019) found green spaces with lower cleanliness levels were associated with higher prevalence of self-reported poor health in Sheffield, UK. Garrett et al., (2019) found that perceived safety and perceived presence of wildlife were associated with recalled well-being following a visit to blue space for residents in Hong Kong. de Bell *et al.* (2020a) found psychological benefits associated with improved ecological health in bluespaces. Pretty et al., (2005) found greater restorative benefits from pleasant (i.e. clean, aesthetically pleasing) environments. Zhang et al., (2017) used accessibility and usability of green spaces to infer quality, and an additional six-item instrument in a questionnaire to elicit perceived quality by residents. They found neither of these measures to be associated with well-being, although they suggest that they impact well-being by improving levels of neighbourhood satisfaction. Akpinar (2016) also interviewed individuals to capture perceived green space quality, using questions relating to aesthetic, cleanliness, maintenance, largeness, shaded areas, lights, and openness/visibility. They found only largeness and openness/visibility were related to improved mental and physical health. Ayala-Azcárraga et al., (2019) found that the perceived height of trees and perceived presence of bird song were the best environmental variables of parks in Mexico City to predict subjective well-being of visitors.

There is also evidence to suggest that the ecological quality or biodiversity of urban natural spaces is important, with more biodiverse environments related to higher levels of health and well-being (Clark *et al.* 2014; Lovell *et al.* 2014). For example, Cameron et al., (2020) found a positive relationship between both avian biodiversity and habitat diversity with self-reported happiness in green spaces in Sheffield, UK. Wood et al., (2018) found park biodiversity measures, such as species richness, habitat diversity and tree canopy cover, were positively related to psychological restorativeness in parks in Bradford, UK. Lindemann-Matthies and Matthies, (2018) found a positive association between plant species richness and stress levels of park visitors in Zurich, Switzerland. However, many other studies find a weak or non-significant relationship. Fuller et al., (2007) found a positive relationship between psychological well-being and plant species, richness and bird species richness, but no correlation with butterfly species richness. Dallimer et al., (2012) found no relationship between well-being and tree canopy or bird species richness. Luck et al., (2011) found a positive relationship between vegetation cover and subjective wellbeing, but only a weak positive relationship with bird species richness and abundance. Taylor et al., (2018) found an association between general well-being and NDVI (Normalised Difference Vegetation Index; mean and standard deviation, the latter as a proxy for biodiversity) in Australia but not for bird species richness, and the association only occurred in two of their four study cities (Hunter & Luck 2015). The relationship between ecological quality of green/blue spaces and well-being is unclear, and more research is required to understand how we best measure biodiversity (Lovell *et al.* 2014; Pett *et al.* 2016).

An alternative measure of ecological quality is the protected designation of a site. Designation of a site implies a level of significant natural importance and biodiversity. Wheeler et al. (2015) use protected area designation, as well as land use categories, bird species richness, water quality, to represent quality of the natural environment in England. They use common designations in the UK as their protected areas layer (Sites of Special Scientific Interest, Special Areas of Conservation, Special Protection Areas, Local Nature Reserves, National Nature Reserves and Ramsar designated wetlands). Protected designation implies a level of ecological quality and they find positive associations between proximity to protected sites and self-reported good health, and similarly negative associations with self-reported bad health. Wyles et al., (2019) find protected designation status of a green or blue space is associated with greater psychological restoration and feeling more connected to nature. Pasanen et al., (2019) found that visits to urban and coastal greenspaces were more restorative when the site had protected status for adults in England. Because accurately quantifying biodiversity of a site has known issues, such as observer bias (Isaac & Pocock 2015; Troudet *et al.* 2017) using a categorisation that implies biological quality may be a good alternative.

Alternatively, access to a private open space may be important for well-being, particularly when considering the importance of, and potential lack of, access to public open spaces in urban areas. Domestic gardens have been found to provide many health and well-being benefits to humans (Brindley *et al.* 2018; Cameron *et al.* 2012; de Bell *et al.* 2020b; de Vries *et al.* 2003). Gardens provide direct and immediate opportunities to interact with nature, and represent an important part of urban green infrastructure. Access to a domestic, and therefore private, garden may also influence the relationship between well-being and public natural environments. For example, access to private open space might substitute the importance of public open spaces (de Bell *et al.* 2020b). Alternatively, gardens may be particularly important to individuals in large urban areas, where access to public natural spaces may be restricted. Or conversely public open spaces may be particularly important to individuals in highly compact urbanised environments that do not accommodate large domestic garden sizes. Additionally, public natural spaces may offer different types of nature experience to a domestic garden (Shanahan *et al.* 2014). For example, nature experiences in a private garden may be solitary or even passive (Coldwell & Evans 2018), or connected to activities such as gardening (Cameron *et al.* 2012; de Bell *et al.* 2020b). Private spaces may also be associated with feelings of security and ownership (de Bell *et al.* 2020b).

The well-being importance of private gardens compared to public green spaces has only been explored in a small handful of studies. Mavoa et al. (2019) found that access to a domestic garden (referred to as "greenness on private land") in urban areas of Melbourne, Australia, was more strongly positively correlated with subjective well-being than public greenspace. Dennis and James, (2017) found the proportion of an LSOA designated as domestic garden in north-west England has a greater effect size when mitigating poor health status than that of public green space. In The Netherlands, de Vries et al., (2003) found having a garden was associated with better mental health (measured by GHQ) but only for those individuals living in the very strongly urban municipalities. Additionally, upon adding the effect of surrounding greenspace into their model, the garden coefficient was not affected. They suggested this might indicate that private gardens had a different well-being effect to public greenspace. de Bell et al., (2020) went further to show that in a representative population sample in England, those who had access to, and used, their private garden were more likely to visit public outdoor spaces than those who did not. All of these studies suggest that access to private open space in urban areas is important for individual well-being, and that it provides different benefits to access to public open areas. A better understanding of how private natural environments affect the relationship between wellbeing and public natural sites is required, particularly in urban environments where exposure to nature is limited.

Much research that explores the proximity of individuals to public open space is conducted at the neighbourhood level, using neighbourhood composition statistics or population-weighted centroids to represent residential location (Garrett *et al.* 2019a; Wheeler *et al.* 2015; White *et al.* 2013b). Other studies use postcode or zipcode centroids as location identifiers. A postcode unit is much more spatially accurate, representing part of a street or an individual building (dependent on mail volume). This highly accurate location is seen as the gold standard in health research (Mizen *et al.* 2015) but is often difficult to obtain due to disclosure issues. It is possible that using aggregated spatial information introduces error in the exposure estimation, as it does not accurately reflect an individual's actual proximity to open spaces. This might explain why some studies do not find any association between well-being and open spaces.

In July 2019, London became the world's first National Park City. This makes it a particularly interesting urban area to study as it has a current agenda to improve the quality and use of its natural environments. London is ranked tenth across 30 global cities, by public greenspace percentage area per capita (World Cities Culture Forum 2017). It is approximately comparable to Rome, Madrid and Rio de Janeiro, and above New York and Berlin. Londoners also enjoy greater access to public greenspace than the national average; 44% of Londoners living within a five-minute walk of a park, compared to 28% of people across Britain (Office for National Statistics 2020b). However, Greater London is a large and densely populated city; London's land area represents only 0.65% of the UK's total land area but is home to 13.36% of the UK's total population. Londoners have just 18.96 m^2 of provision per person, which is almost half the national average (Fields in Trust 2020). London supports a wide diversity of wildlife habitats, with over 13,000 species recorded over the last 50 years (London Wildlife Trust 2015). These habitats are threatened with loss or damage by development pressures and without protection and management, the overall quality of London’s natural environment is likely to be damaged over time (London Wildlife Trust 2015).

4.2.1 Key questions and approach

In this study we ask five key questions:

1. Is residential proximity to a high quality public natural open space (SINC), associated with higher levels of well-being
2. Is residential proximity to all public natural open spaces (POSs) associated with higher levels of well-being?
3. Is access to a private open space associated with higher levels of well-being?
4. Does having access to a private space affect the relationship between proximity to SINCs and POSs, and well-being?
5. Does the spatial accuracy of the residential location affect our findings?

We use highly detailed and up-to-date datasets in London, UK to give us locations and categorisations of all locations deficient in access to public open spaces in the city. In this study, we determine if proximity to a site of high ecological quality is associated with higher levels of well-being in London. We do this by using areas of the city that are termed as ‘deficient in access to nature’ and examine if living in these areas is associated with a reduction in self-reported well-being. Areas of deficiency to nature mapping gives an indication of whether people living in a given area can easily visit wildlife sites. It is often a more meaningful measure of people’s access to nature than simply calculating the total number of relevant sites (or their total land area), because it accounts for the distribution of sites around an individual’s residence and acknowledges the effect of sites in neighbouring areas.

We use a designation of public open space in London called Sites of Importance for Nature Conservation (SINCs) to identify green and blue spaces that have significant wildlife value, and therefore a higher level of site quality. We use a dataset that uses a novel method for estimating proximity, and deficiency, to these sites, using network analysis tools to model walking distances along actual routes to known entry points of each SINC, therefore giving a highly accurate measurement of access. We then repeat the analysis for all public open spaces, and see if the relationships are similar when quality of site is not a factor. We also include access to private space to account for the different ways in which individuals may be exposed to nature in a highly urbanised area.

Areas of deficiency mapping is used by Local Councils to assess open space provision in their boroughs. The London Plan, a policy document which sets out the development framework for London, states that Local Councils should reduce deficiency in access to open space and to nature; to achieve this, they need to know where the deficient areas are and understand their causes (Greater London Authority 2016). AoD to SINCs can be reduced in different ways: by creating more sites or by expanding their area; by improving the quality of open spaces so that they become relevant as SINCs; or by improving access to existing sites by adding gates, removing access restrictions or improving local walking routes.

We use a large sample size of individuals from the British Household Panel Survey (BHPS) and identify their residential location using their 6-digit postcode unit. We also repeat the analysis using the equivalent LSOA population-weighted centroid to establish the significance of any estimation error in the models using a more aggregated identifier. Many studies that examine the relationship between well-being and green/blue spaces conduct cross-sectional analysis. This approach, while contributing significantly to our understanding, carries endogeneity issues which make the inference of causality difficult. Using longitudinal data and fixed effects regression allowed us to reduce endogeneity bias in our analysis (White *et al.* 2013b). Here we use a large sample size of individuals from a large panel dataset, which allows us to employ longitudinal well-being data. We take advantage of the panel nature of the data by using fixed effects. Fixed effects have a significant advantage over cross-sectional correlations as it allows us to isolate within-person variation as opposed to between-person variation. We effectively follow the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits) that could be related to both proximity to natural environments and subjective well-being.

We use two measures of subjective well-being: life satisfaction and the General Health Questionnaire (GHQ). There is a large body of research that examines the reliability and validity of measures of subjective well-being (Diener *et al.* 2013; Frey *et al.* 2010). Despite several potential limitations, subjective measures of well-being have been shown to have a high scientific standard in terms of internal consistency, reliability and validity (Frey *et al.* 2010; OECD 2013). Life satisfaction, and mental health are both commonly used measures in well-being surveys, and well-being and nature literature (White *et al.* 2013b). The General Health Questionnaire (GHQ) is a screening tool which helps to diagnose mood disorders. It is widely used in literature as a measure of mental health (Gascon *et al.* 2015). We also make use of a suite of socio-demographic and spatial explanatory variables available to us, both in the survey data and that which is publicly available, to address our research questions.

4.3 Methods

4.3.1 Study site

London is the capital and largest city in the UK, and Greater London covers an area of 1,572 km^2. Greater London, or the Greater London Built-up Area, is often used for administrative statistics and refers to the continuous urban area. This includes the City of London, 12 London boroughs, and 20 Outer London boroughs. In 2019, the UK Office for National Statistics (ONS) estimated Greater London's population at 8.962 million, with a population density of 5,701 individuals per km^2 (ONS 2020).

Approximately 47% of Greater London is considered 'green' (Greenspace Information for Greater London CIC, 2019). 33% of London is classed as natural habitat within open spaces, and an additional 14% is estimated to be vegetated private, domestic garden land. A further 10% of Greater London is private, domestic garden land (not vegetated). Over 2% of Greater London's area is categorised as blue space, such as rivers, canals and reservoirs. There are 1,602 SINCs in Greater London covering 18.97% of the city's area. Public open spaces account for 17.99% of Greater London.

4.3.2 Sites of Importance for Nature Conservation

In this study we use two key datasets regarding London's natural environments: Sites of Importance for Nature Conservation (SINCs; Figure 4.1), and Areas of Deficiency to SINCs (AoD to SINCs; Figure 4.2). These datasets are produced and maintained by Greenspace Information for Greater London CIC (GiGL). SINCs are open spaces that have significant biodiversity importance, regardless of ownership. It is a land-use designation, identified through objective survey and evaluation, and affords levels of protection within the planning system (London Wildlife Trust 2015). It is recognised at the local authority level, and each authority is responsible for identifying and inventorying all sites of conservation importance within their area.

GiGL define an AoD to SINCs as '*Areas where people have to walk more than one kilometre to reach an accessible wildlife site of importance'* (Greenspace Information for Greater London CIC 2019a). The 1 km walking distances for (Metropolitan and District) SINCs is given in The Mayor's Biodiversity Strategy (2002). To calculate the AoD dataset, AoD to Nature is modelled only for District and Metropolitan grade SINCs. Sites which have national or international statutory wildlife conservation designations (e.g. Special Protection Areas) are also included in the model as Metropolitan grade SINCs. Actual walking distance has been modelled around each SINC, using all possible travel routes such as roads, bridges, and paths from known SINC access points, using an automated approach based on RouteFinder GIS. This creates 'isotimes' surrounding each site, all locations that can be reached within 1 km of known SINC access points, and any location outside of these is designated as part of the AoD to SINCs. It is possible for a location adjacent to a SINC to be categorised as deficient, if the SINC does not have an access point within a 1 km walk of that point. This is particularly common for very big sites, and in areas with lots of railway lines.

An expert panel advised on which SINCs should be included in the calculation of the AoD to Nature, with Local Authority representatives providing expert judgement on the quality of sites. SINCs had to meet specific criteria; because they had to be publicly accessible, undeveloped Green Belt was usually excluded. Where only part of a site is both accessible to the public and good for wildlife, only that part is included in the AoD model; and if a SINC is designated solely on account of a particular inconspicuous species or specialist interest, it may not have been included.

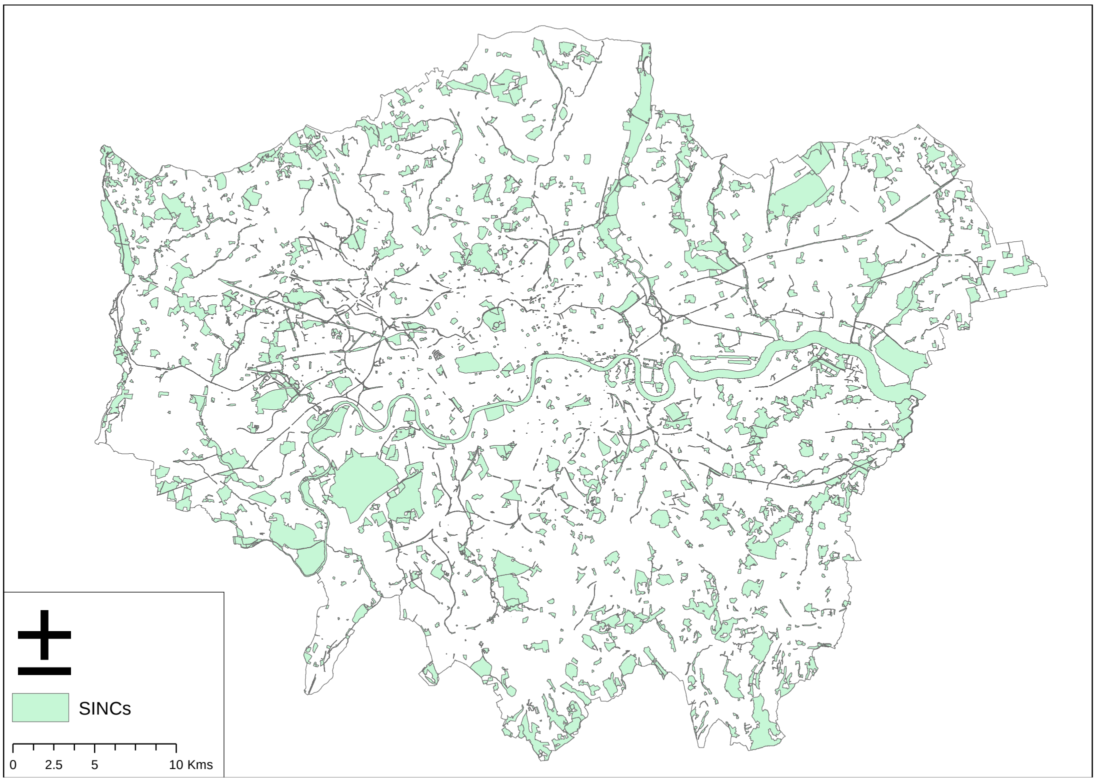

Figure 4.1. Sites of Importance for Nature Conservation (SINCs), as maintained by Greenspace Information for Greater London CIC (GiGL) [obtained 12th December 2019].

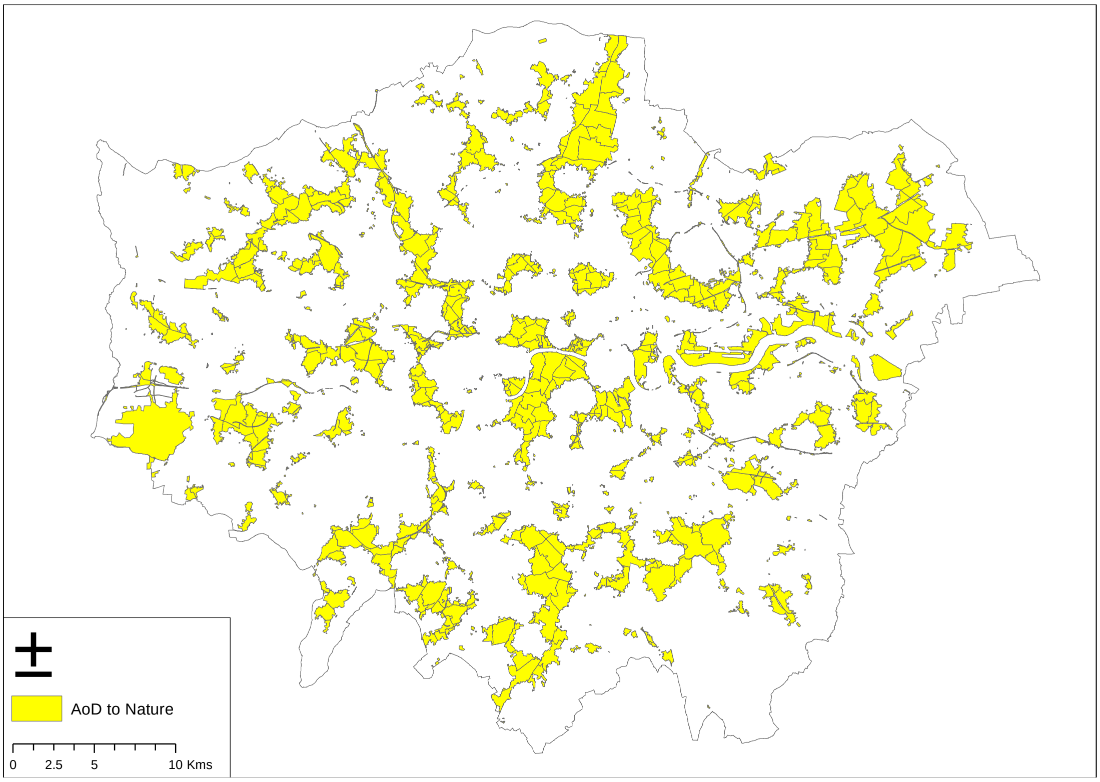

Figure 4.2. Areas of Deficiency to Sites of Importance for Nature Conservation (AoD to SINCs), as maintained by Greenspace Information for Greater London CIC (GiGL) [obtained 12th December 2019].

4.3.3 Public open spaces (POSs)

POSs are described as any open area available to the public, and like the SINC database, are held and maintained by GiGL, with data provided by each London borough. Green and blue POSs are identified using the PPG17 categorisation (Planning Policy Guidance 17), which sets out broad category types for open spaces based on their size, facilities and local importance. There are seven categories of POS, and each has a maximum walking distance to which every home in London should be situated. The walking distances for the POS, like the 1km distance to SINCs, are based on current advice and understanding, and are set out in Policy 7.18 of the London Plan (GLA, 2016; see Table S4.1 in appendix).

AoD to POS are areas above a certain walking distance from POSs that meet the criteria set out in The London Plan (Figure 4.3). AoD to POS consist of four layers, one for each designation of park size: Local, District, Metropolitan, and Regional (pocket parks, small and local open spaces are grouped together into the Local category, and linear spaces are removed). Each AoD to POS layer uses a different respective walking distance to reflect their differing designations. AoD to SINCs use Metropolitan and District SINCs only, and are calculated using a 1 km walking distance. Therefore, this is a conservative distance, given the large size and importance of several SINCs. Modelling smaller POSs with a 1km walking distance is not effective, as the majority of Greater London meets this criteria. Additionally, higher grades of POS count towards alleviating AoD to lower grades, so if a pixel is not within a specified walking distance for a District park, but is within that distance from a Regional park, then this does not count as AoD to District parks, because an individual can visit the Regional park instead. This means that AoDs to SINCs are actually a more conservative estimate of proximity than the AoDs to POS.

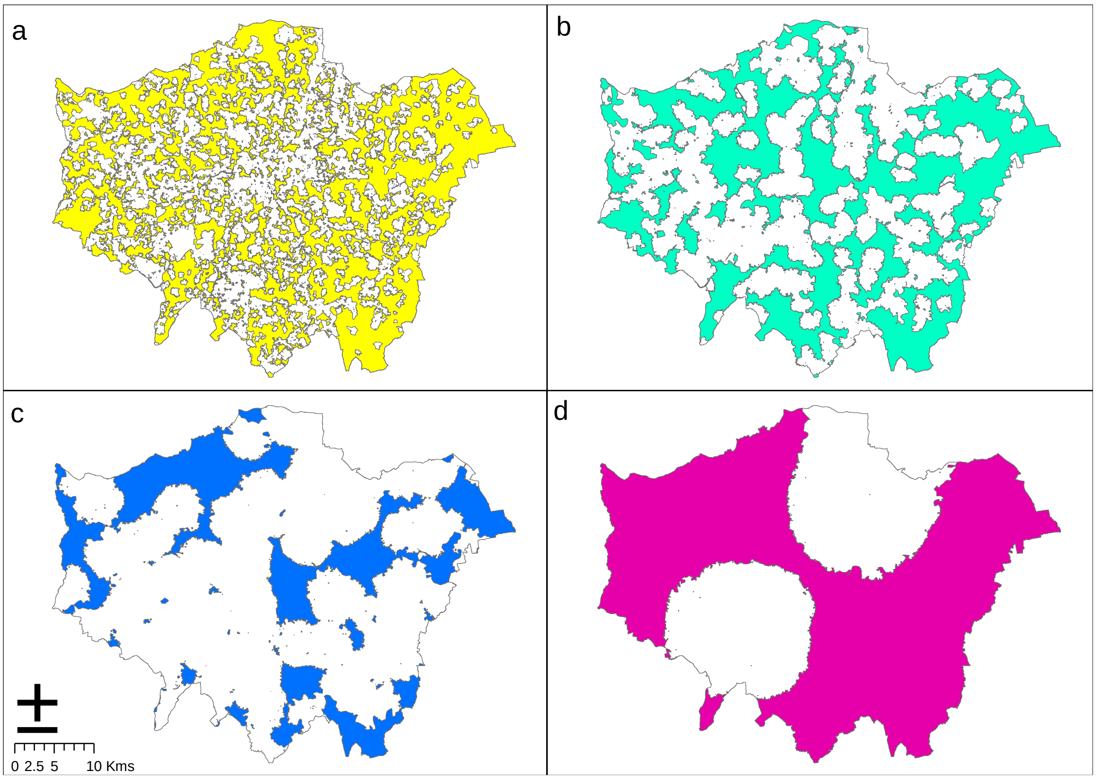

Figure 4.3. Areas of Deficiency to Public Open Spaces (AoD to POS), by Greenspace Information for Greater London CIC (GiGL) [Dataset obtained: 7th June 2019]. AoD to a) Small, Local and Pocket parks, b) District parks, c) Metrolipolitan parks, and d) Regional parks.

4.3.4 Study population

We used the British Household Panel Survey (BHPS) which is available as part of the Understanding Society project (University of Essex. Institute for Social and Economic Research 2019b, 2019a). The BHPS is a large multi-year panel survey collecting individual and household information from a representative sample population. Demographic, socio-economic, health and geographic data are collected in the dataset, as well as that pertaining to attitudes, opinions, and values. The BHPS ran from 1991 to 2018 (waves 1-18) and collected information from over 10,000 individuals (5000 households). Data collection for each wave in the BHPS was undertaken within a sample year.

Each individual in the BHPS has a geographic identifier as an easting and northing (centroid of the postcode unit). A postcode unit can represent part of a street or an individual building (dependent on mail volume). This highly specific location data was accessed using the UK Data Service Secure Lab environment to ensure data protection due to the highly disclosive nature of the geographic location data. We included all adults (categorised as 16+ years) with eastings and northings pertaining to Greater London in this study.

4.3.5 Well-being

Life satisfaction is based on the respondents' answer to the following questions: 'How dissatisfied or satisfied are you with life overall?' Respondents give a single reply from a Likert scale with options ranging from 7 ('completely satisfied') to 1 ('completely unsatisfied'). To measure mental health we used the 12-item short form of the GHQ. Respondents are asked to self-assess against six positive and six negative statements (e.g. I am capable of making decisions and I think of myself as worthless). Respondents give a single reply to each statement on a four-point scale, based on their own evaluation of how the "past few weeks" compare with "usual". The scale ranges from 0 (not at all), 1 (no more than usual), 2 (rather more than usual), and 3 (much more than usual). This gives an overall score ranging from 0 (very low mental distress) to 36 (very high mental distress).

Both measures are captured in the BHPS and the population sample is shown in Figure 4.4. The GHQ is asked in all 18 waves of the BHPS but the life satisfaction question is only asked in 12 waves. Therefore the number of observations in the life satisfaction model is lower. Missing data across all variables can be found in the BHPS and is due to wave nonresponse, item nonresponse, and respondent attrition. Where possible and appropriate we have imputed missing values from adjacent waves.

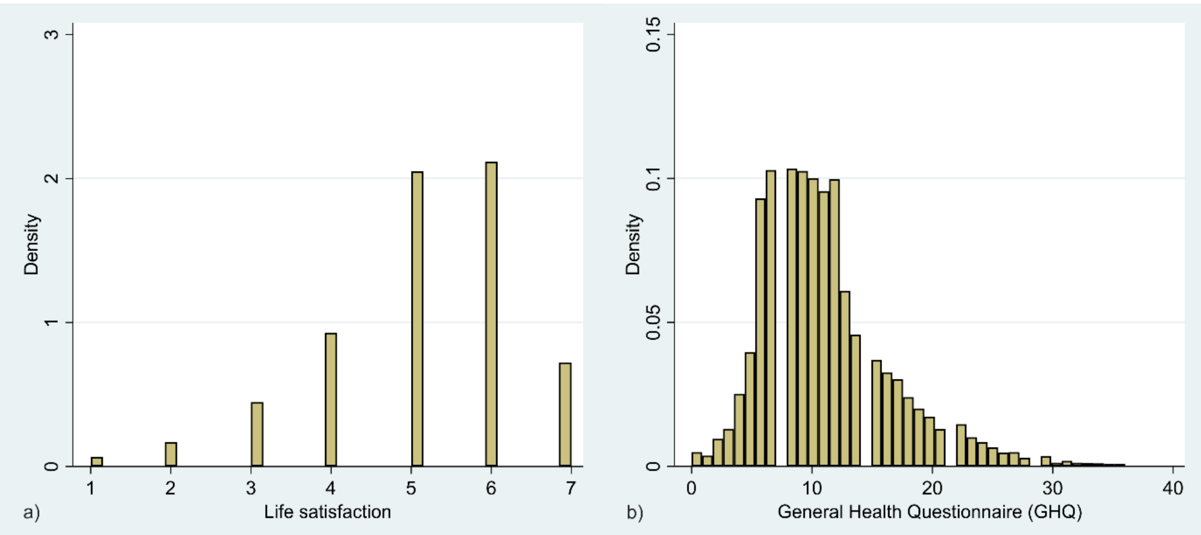

Figure 4.4. The distribution of subjective well-being across the population sample. a) Life satisfaction, and b) GHQ. The y-axis represents the density of observations per bin: the height of the bars are scaled so that the sum of their areas equals 1.

4.3.6 Private open space

We include the BHPS variable: access to a private garden/terrace. Respondents reply yes or no to the question: "Does this accommodation have a place to sit outside e.g. a terrace or garden?" This question was asked in 13 of the 18 waves in the BHPS.

4.3.7 Control data

We included commonly observed predictors of an individual's subjective well-being in our regression analysis (see Dolan *et al.* (2008) for a review of this literature). These include individual-, household-, and neighbourhood- level factors. Specifically at the individual level we use age, higher education, relationship status, health, labour force status, commuting time and liking one's neighbourhood. At the household level we use income, living with children, residence type and household space. A wave variable was included to account for any natural temporal progression in the data (Luechinger 2010). Table 4.3 provides a description of each variable and Table 4.4 details the descriptive statistics for each variable in the total dataset for Greater London, and also that pertaining to the estimation samples for each model. We can see that each model is very similar to the overall BHPS and UKHLS samples.

It is likely that the relationship between well-being and public natural environments is affected by socio-economic factors pertaining to neighbourhoods. Therefore we included the English Indices of Multiple Deprivation. These are calculated every 2-5 years by the Department for Communities and Local Government (DCLG), and are based on 37 separate indicators, organised across seven distinct domains of deprivation (Department for Communities and Local Government 2010). In this analysis we included the Income Deprivation domain and the Employment Deprivation domain, which measure the proportion of the population experiencing deprivation relating to low income and benefit claiming respectively. We also included the Crime Deprivation domain which reflects the risk of personal and material victimisation, and the Education Deprivation domain which relates to school performance and higher education rates.

The indices of deprivation are only available down to the lower super output area (LSOA) level (4,765 LSOAs in London). LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). The mean area of a London LSOA is 3.3km^2. Due to population fluctuations approximately 5% of LSOAs in the UK changed in 2011 (split, merged or deleted), so here, for consistency, we used the 2002 LSOA structure throughout the study.

It is also possible that air pollution levels affect the relationship between green/blue spaces and well-being (Laffan 2018; Yuan *et al.* 2018). Here we included annual ambient outdoor NO_2 levels from the UK's Department for Environment, Food and Rural Affairs (Defra) as pollution-climate modelled values (Defra 2016). These are outputs based on dispersion modelling using point sources of known emission levels (e.g. monitoring stations, power stations, roadsides) and UK meteorological data, and are available as 1km x 1km grids for the UK as the annual mean NO_2 in µg/m^3. Each LSOA was given the pollution value of the nearest NO_2 point to each LSOA population-weighted centroid for the year 2008. The pollution values were then attributed to every individual residing in the corresponding LSOA.

4.3.8 Statistical analysis

Every individual's residential postcode location was assigned as being either inside (0) or outside (1) an AoD to SINCs (we inverted this so that a positive coefficient indicated better access to SINCs). This was repeated for every wave of the BHPS, creating a longitudinal dataset of access to SINCs for every participant in the sample. We then constructed regression models to examine the relationship between subjective wellbeing and access to SINCs. We built four model specifications (Table 4.1). The basic specification examined the effect of proximity to nature, adjusting for a range of control variables, for both life satisfaction (model 1) and the GHQ (model 2). To test for possible effects of access to private open space, the specifications were extended to include "Access to private space" (models 3 and 4).

We constructed the equation using fixed effects regression:

$$SW_{ijt} \;=\; \beta_0 \;+\beta_1 A_{jt} \;+\beta_2 L_{jt} + \beta_3 X_{it} + \beta_4 T_t + \varepsilon_{ijt}$$

Where SW is a measure of subjective well-being (life satisfaction or GHQ), for an individual *i*, at a given location *j* and in a given year *t*. It is a function of living outside an AoD (A_{jt}), a vector of LSOA neighbourhood factors (L_{jt}) and individuals' socio-economic and demographic characteristics (X_{it}), and a wave variable (T_t). ε_{ijt} is the error term (all remaining unaccounted for variation).

All analysis was carried out in the UK Data Service Secure Lab environment. Spatial analysis was carried out using ArcGIS v10 (ESRI 2011) and regression analysis using the regress and xt suites in Stata 16 software (StataCorp 2019).

Table 4.1. Model specifications.

Model	Dependent variable	Model specification
1	Life satisfaction	Access to SINCs + control variables
2	GHQ	Access to SINCs + control variables
3	Life satisfaction	Access to private open space + control variables
4	GHQ	Access to private open space + control variables
5	Life satisfaction	Access to SINCs + access to private open space + control variables
6	GHQ	Access to SINCs + access to private open space + control variables

To further examine the relationship between POS and subjective well-being, we repeated models 1, 2, 5 and 6, replacing the AoD to SINCs with the AoD to POS layers (
Table 4.2). This allowed us to examine a further question: do we find the same relationships with well-being when we look at all POS and not just those of high ecological quality? We used the AoD to POS layers for each category of POS (local, district, metropolitan and regional), which also allows us to test if the provision and accessibility of POS in London is effective at providing well-being benefits for its residents.

Table 4.2. Model specifications for POS analysis.

Model	Dependent variable		Model specification
7	Life satisfaction	a	Local POS + control variables
		b	District POS + control variables
		c	Metropolitan POS + control variables
		d	Regional POS + control variables
8	GHQ	a	Local POS + control variables
		b	District POS + control variables
		c	Metropolitan POS + control variables
		d	Regional POS + control variables
9	Life satisfaction	a	Local POS + access to private open space + control variables
		b	District POS + access to private open space + control variables

		c	Metropolitan POS + access to private open space + control variables
		d	Regional POS + access to private open space + control variables
10	GHQ	a	Local POS + access to private open space + control variables
		b	District POS + access to private open space + control variables
		c	Metropolitan POS + access to private open space + control variables
		d	Regional POS + access to private open space + control variables

4.3.9 Sensitivity testing

We repeated the analysis again using LSOA population-weighted centroids instead of postcode unit centroids. This allowed us to test whether analysis at the LSOA-level achieves the same relationships and allowed us to assess different measures of neighbourhood. LSOAs are frequently used as a neighbourhood boundary to investigate relationships between residential natural environments and health and well-being.

Table 4.3. Variable descriptions.

	Variable description
Life satisfaction	Respondent’s self-reported life satisfaction (scale 1 to 7)
GHQ	Respondent’s self-reported General Health Questionnaire score (scale 0 to 36)
Not within AoD to SINCs	Residential easting/northing is within a 1km walk of a Site of Importance for Nature Conservation (yes/no)
Not within AoD to local POSs	Residential easting/northing is within a 400m walk of a local public open space (yes/no)
Not within AoD to district POSs	Residential easting/northing is within a 1.2km walk of a district public open space (yes/no)
Not within AoD to metropolitan POSs	Residential easting/northing is within a 3.2km walk of a metropolitan public open space (yes/no)
Not within AoD to regional POSs	Residential easting/northing is within a 8km walk of a regional public open space (yes/no)
Access to private open space	“Does this accommodation have a place to sit outside e.g. a terrace or garden?” (yes/no)
Spatial control variables	
Income deprivation	Indices of Multiple Deprivation – deprivation relating to low income and social benefit in the LSOA
Employment deprivation	Indices of Multiple Deprivation – deprivation relating to benefit claimants in the LSOA
Education deprivation	Indices of Multiple Deprivation – deprivation relating to school performance and higher education rates in the LSOA
Crime deprivation	Indices of Multiple Deprivation – deprivation relating to the risk of personal and material victimisation in the LSOA
NO_2	Mean annual ambient nitrogen dioxide (NO_2) in respondent’s residential LSOA in 2008 ($\mu g/m^3$)
Age (yrs)	
16-25	Respondent’s age is between 16-25 years (yes/no)
26-35	Respondent’s age is between 26-35 years (yes/no)
36-45	Respondent’s age is between 36-45 years (yes/no)
46-55	Respondent’s age is between 46-55 years (yes/no)
56-65	Respondent’s age is between 56-65 years (yes/no)
66-75	Respondent’s age is between 66-75 years (yes/no)
75+	Respondent’s age is between 75+ years (yes/no)
University-level qualification	Respondent has a university –level qualification (yes/no)
In a relationship	Respondent is married or living as a couple (yes/no)
Living with children	Living with own children (<16 years old) (yes/no)
Annual household income	Log equivalent annual household income (income divided by square root of household size (number of people))

Health condition	Respondent self-reports a health condition that limits the type of work or amount of work they can do (yes/no)
Neighbourhood satisfaction	“Overall, do you like living in this neighbourhood?” (yes/no)
Employment status	
Employed	Respondent is employed (yes/no)
Unemployed	Respondent is unemployed or disabled (yes/no)
Retired	Respondent is retired (yes/no)
Caring for family	Respondent is caring for family (yes/no)
In training	Respondent is in training (yes/no)
Other	Respondent is in another type of status (yes/no)
House type	
Detached	Respondent lives in a detached house (yes/no)
Semi-detached	Respondent lives in a semi-detached house (yes/no)
Terraced	Respondent lives in a terraced house (yes/no)
Flat	Respondent lives in a flat (yes/no)
Other	Respondent lives in another type of dwelling e.g. bedsit (yes/no)
Household space	
<1 room per person	Less than 1 room per person in the house (yes/no)
1 - < 3 rooms per person	Between 1 and under 3 rooms per person in the house (yes/no)
3 ≥ rooms per person	Three or more rooms per person in the house (yes/no)
Commuting time	
None	Respondent has no commute (yes/no)
≤ 15 mins	Respondent has a commute of 15 minutes or less (yes/no)
16-30 mins	Respondent has a commute of 16-30 minutes or less (yes/no)
31-50 mins	Respondent has a commute of 31-50 minutes or less (yes/no)
≥ 50 mins	Respondent has a commute of over 50 minutes (yes/no)
Other	
Wave	BHPS wave (1-18)

Table 4.4. Descriptive statistics.

	All BHPS		Life satisfaction models	GHQ model 2	GHQ models 4 & 6
	N (total) N=15,682	Mean (St. Dev.) or %	Mean (St. Dev.) or % N=8,388	Mean (St. Dev.) or % N=13,484	Mean (St. Dev.) or % N=9,139
Life satisfaction	9,138	5.15 (1.25)	5.14 (1.26)	-	-
GHQ	14,301	11.18 (5.41)	-	11.22 (5.41)	11.22 (5.46)
Not within AoD to SINCs	15,682	68.11%	68.48%	67.97%	68.49%
Not within AoD to local POSs	15,682	46.03%	47.17%	45.61%	47.12%
Not within AoD to district POSs	15,682	51.35%	51.36%	51.07%	51.45%
Not within AoD to metropolitan POSs	15,682	81.21%	80.97%	80.78%	80.97%
Not within AoD to regional POSs	15,682	47.20%	46.42%	46.95%	46.49%
Access to private open space	10,223	86.64%	86.78%	-	86.76%
Spatial control variables					
Income deprivation	15,682	0.17 (0.10)	0.16 (0.46)	16.32 (0.10)	16.24 (0.10)
Employment deprivation	15,682	0.09 (0.04)	0.09 (0.04)	0.09 (0.04)	0.09 (0.04)
Education deprivation	15,682	13.77 (10.74)	13.49 (10.61)	13.62 (10.69)	13.54 (10.72)
Crime deprivation	15,682	0.35 (0.59)	0.34 (0.60)	0.35 (0.59)	0.34 (0.60)
NO_2	15,682	28.73 (5.90)	34.65 (6.54)	34.75 (6.60)	34.64 (6.57)
Age (yrs)					
16-25	15,682	17.71%	16.21%	17.26%	16.33%
26-35	15,682	21.56%	20.45%	21.57%	20.45%
36-45	15,682	18.24%	18.75%	18.41%	18.88%
46-55	15,682	16.21%	15.86%	16.02%	15.69%
56-65	15,682	12.00%	13.47%	12.40%	13.42%
66-75	15,682	7.93%	9.04%	8.34%	8.97%
75+	15,682	6.34%	6.22%	6.00%	6.26%
University-level qualification	15,098	27.75%	30.66%	28.38%	30.66%
In a relationship	15,676	58.03%	58.92%	58.62%	58.84%
Living with children	15,682	24.00%	23.19%	24.06%	23.42%
Annual household income	15,176	7.18 (0.84)	7.32 (0.83)	7.19 (0.84)	7.31 (0.85)
Health condition	15,610	16.22%	15.98%	16.25%	16.03%
Like neighbourhood	14,712	88.76%	89.76%	88.79%	89.74%
Employment status					
Employed	15, 613	61.34%	62.35%	61.36%	62.32%
Unemployed	15, 613	7.06%	6.25%	6.95%	6.17%
Retired	15, 613	16.17%	17.45%	16.45%	17.51%
Caring for family	15, 613	7.92%	7.22%	7.98%	7.13%
In training	15, 613	6.95%	6.18%	6.82%	6.30%
Other	15, 613	0.56%	0.55%	0.44%	0.57%
House type					
Detached	15,030	6.81%	9.68%	6.94%	7.65%
Semi-detached	15,030	25.40%	23.29%	25.82%	25.37%
Terraced	15,030	34.88%	36.35%	35.21%	36.35%

Flat Other	15,030 15,030	30.88% 2.02%	29.18% 1.50%	30.70% 1.33%	29.11% 1.52%
Household space					
<1 room per person 1 - < 3 rooms per person 3 ≥ rooms per person	15, 275 15, 275 15, 275	7.55% 77.55% 14.90%	6.83% 76.35% 16.82%	7.34% 77.37% 15.29%	6.74% 76.38% 16.88%
Commuting time					
None ≤ 15 mins 16-30 mins 31-50 mins ≥ 50 mins	14,427 14,427 14,427 14,427 14,427	41.77% 16.05% 16.75% 12.41% 13.01%	40.23% 15.89% 17.05% 12.86% 13.97%	41.05% 16.19% 17.01% 12.57% 13.18%	40.23% 15.88% 17.10% 12.80% 13.99%
Other					
Wave	15,682	-	-	-	-

4.4 Results

4.4.1 Areas of Deficiency to SINCs

Life satisfaction

We find that living within a 1km walk of a SINC in Greater London increases an individual's life satisfaction by 0.117 points on a scale of 1 to 7 (

Table 4.5, model 1; b=0.117, p=0.047). When we standardise the regression coefficients (z-scores), we are able to compare the effect size of proximity to SINCs with that of other variables in our analysis (Table 4.6). Using standardised coefficients, we find that the effect size of living within a 1km walk from a SINC (β=0.043) is half that of being in a relationship (β=0.104), or similar to the negative effect size of being unemployed, when compared to being employed (β=-0.055).

Table 4.5. Areas of Deficiency to SINCs regression results, showing unstandardised coefficients.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
Not within AoD to SINCs	**0.117***	**0.501***	**-**	**-**	**0.120***	0.248
	(0.059)	**(0.205)**	**-**	**-**	**(0.059)**	(0.267)
Access to private open space	-	-	**0.180*****	**-0.687****	**0.182*****	**-0.683****
	-	-	**(0.049)**	**(0.221)**	**(0.048)**	**(0.221)**
Spatial control variables						
Income deprivation	-0.709	**-5.315***	-0.749	-2.220	-0.647	-2.066
	(0.718)	**(2.629)**	(0.716)	(3.245)	(0.718)	(3.250)
Employment deprivation	2.405	8.712	2.245	2.956	2.223	2.989
	(1.335)	(4.807)	(1.335)	(6.042)	(1.335)	(6.042)
Education deprivation	-0.005	0.018	-0.004	0.012	-0.005	0.011
	(0.004)	(0.014)	(0.004)	(0.017)	(0.004)	(0.017)
Crime deprivation	-0.081	-0.003	-0.067	0.106	-0.075	0.090
	(0.060)	(0.203)	(0.060)	(0.269)	(0.060)	(0.269)
NO_2	0.001	**0.038***	0.003	0.015	0.004	0.017
	(0.006)	**(0.019)**	(0.006)	(0.027)	(0.006)	(0.027)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.373****	0.469	**-0.385****	0.901	**-0.377****	0.918
	(0.123)	(0.442)	**(0.123)**	(0.554)	**(0.123)**	(0.554)
26-35	**-0.312*****	0.637	**-0.317*****	**0.916***	**-0.312*****	**0.926***
	(0.092)	(0.329)	**(0.092)**	**(0.418)**	**(0.092)**	**(0.418)**
36-45	**-0.205*****	**0.483***	**-0.205*****	0.405	**-0.204*****	0.407
	(0.061)	**(0.215)**	**(0.061)**	(0.280)	**(0.061)**	(0.280)
56-65	**0.148***	**-1.022*****	**0.160***	**-1.099*****	**0.155***	**-1.108*****
	(0.063)	**(0.222)**	**(0.063)**	**(0.286)**	**(0.063)**	**(0.286)**
66-75	0.178	**-0.890***	0.189	-0.749	0.185	-0.757
	(0.108)	**(0.381)**	(0.108)	(0.492)	(0.108)	(0.492)
75+	0.076	-0.483	0.078	-0.387	0.077	-0.388
	(0.148)	(0.531)	(0.148)	(0.674)	(0.148)	(0.674)
University-level qualification	**-0.228***	0.108	**-0.229***	0.176	**-0.235***	0.167
	(0.111)	(0.341)	**(0.111)**	(0.502)	**(0.111)**	(0.502)
In a relationship	**0.266*****	**-0.493****	**0.261*****	-0.349	**0.268*****	-0.336
	(0.052)	**(0.182)**	**(0.052)**	(0.237)	**(0.052)**	(0.237)
Living with children	-0.056	-0.149	-0.059	-0.380	-0.056	-0.376
	(0.052)	(0.178)	(0.052)	(0.235)	(0.052)	(0.235)
Annual household income	-0.013	0.005	-0.013	-0.044	-0.014	-0.046
	(0.020)	(0.075)	(0.020)	(0.086)	(0.020)	(0.086)
Health condition	**-0.398*****	**1.952*****	**-0.397*****	**2.005*****	**-0.396*****	**2.009*****
	(0.044)	**(0.153)**	**(0.044)**	**(0.196)**	**(0.044)**	**(0.196)**
Like neighbourhood	**0.179*****	**-0.329***	**0.179*****	-0.280	**0.177*****	-0.285

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
	(0.047)	**(0.166)**	**(0.047)**	(0.212)	**(0.047)**	(0.212)
Employment status (reference: employed)						
Unemployed	**-0.283***** **(0.071)**	**1.074***** **(0.250)**	**-0.289***** **(0.071)**	**1.142***** **(0.323)**	**-0.287***** **(0.071)**	**1.144***** **(0.323)**
Retired	0.109 (0.075)	**-0.574*** **(0.275)**	0.106 (0.075)	-0.527 (0.342)	0.108 (0.075)	-0.521 (0.342)
Caring for family	0.085 (0.071)	0.187 (0.256)	0.086 (0.071)	0.361 (0.319)	0.087 (0.071)	0.363 (0.319)
In training	-0.018 (0.083)	-0.250 (0.286)	-0.021 (0.083)	-0.675 (0.369)	-0.019 (0.083)	-0.674 (0.369)
Other	**-0.363*** **(0.151)**	0.143 (0.632)	**-0.362*** **(0.151)**	0.640 (0.675)	**-0.364*** **(0.151)**	0.638 (0.675)
House type (reference category: detached)						
Semi-detached	**-0.161*** **(0.076)**	-0.131 (0.277)	**-0.168*** **(0.076)**	0.017 (0.343)	**-0.164*** **(0.076)**	0.028 (0.344)
Terraced	-0.111 (0.082)	-0.264 (0.294)	-0.115 (0.082)	-0.064 (0.369)	-0.117 (0.082)	-0.068 (0.369)
Flat	-0.088 (0.088)	-0.041 (0.317)	-0.064 (0.088)	-0.161 (0.395)	-0.062 (0.088)	-0.155 (0.395)
Other	**-0.345**** **(0.133)**	0.440 (0.484)	**-0.310*** **(0.133)**	0.693 (0.576)	**-0.321*** **(0.133)**	0.680 (0.576)
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.083 (0.064)	**0.554*** **(0.225)**	-0.081 (0.064)	**0.756**** **(0.293)**	-0.082 (0.064)	**0.753*** **(0.293)**
3 ≥ rooms per person	0.020 (0.053)	**-0.464*** **(0.185)**	0.030 (0.053)	-0.253 (0.240)	0.027 (0.053)	-0.261 (0.240)
Commuting time (reference category: None)						
≤ 15 mins	0.025 (0.059)	-0.184 (0.211)	0.024 (0.059)	-0.180 (0.263)	0.025 (0.059)	-0.176 (0.263)
16-30 mins	0.098 (0.058)	**-0.449*** **(0.209)**	0.093 (0.057)	**-0.658*** **(0.257)**	0.097 (0.057)	**-0.649*** **(0.257)**
31-50 mins	0.104 (0.062)	-0.419 (0.224)	0.101 (0.062)	-0.315 (0.275)	0.104 (0.062)	-0.309 (0.275)
≥ 50 mins	0.091 (0.062)	-0.086 (0.226)	0.083 (0.062)	-0.036 (0.276)	0.088 (0.062)	-0.026 (0.276)
Other						
Wave	**-0.016**** **(0.005)**	**0.069***** **(0.017)**	**-0.016**** **(0.005)**	**0.057**** **(0.022)**	**-0.015**** **(0.005)**	**0.057**** **(0.022)**
R^2	0.05	0.03	0.05	0.04	0.05	0.04

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
Observations	8,388	13,484	8,388	9,139	8,388	9,139
Individuals	1,586	2,130	1,586	1,606	1,586	1,606
Mean obs per person	5.3	6.3	5.3	5.7	5.3	5.7
Interaction terms						
Not within AoD to SINCs ## garden	-	-	-	-	-0.064	0.389
	-	-	-	-	(0.096)	(0.437)

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

Table 4.6. Areas of Deficiency to Nature regression results, showing standardised coefficients.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
Not within AoD to SINCs	**0.043***	**0.043***	**-**	**-**	**0.044***	0.021
	(0.059)	**(0.205)**	**-**	**-**	**(0.059)**	(0.267)
Access to private open space	-	-	**0.049*****	**-0.043****	**0.049*****	**-0.042****
	-	-	**(0.049)**	**(0.221)**	**(0.048)**	**(0.221)**
Spatial control variables						
Income deprivation	-0.056	**-0.098***	-0.060	-0.041	-0.052	-0.038
	(0.718)	**(2.629)**	(0.716)	(3.245)	(0.718)	(3.250)
Employment deprivation	0.085	0.071	0.079	0.024	0.078	0.024
	(1.335)	(4.807)	(1.335)	(6.042)	(1.335)	(6.042)
Education deprivation	-0.040	0.036	-0.037	0.023	-0.042	0.021
	(0.004)	(0.014)	(0.004)	(0.017)	(0.004)	(0.017)
Crime deprivation	-0.039	-0.000	-0.032	0.012	-0.035	0.010
	(0.060)	(0.203)	(0.060)	(0.269)	(0.060)	(0.269)
NO_2	0.003	**0.047***	0.016	0.018	0.023	0.021
	(0.006)	**(0.019)**	(0.006)	(0.027)	(0.006)	(0.027)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.109****	0.033	**-0.113****	0.061	**-0.111****	0.062
	(0.123)	(0.442)	**(0.123)**	(0.554)	**(0.123)**	(0.554)
26-35	**-0.100*****	0.048	**-0.102*****	**0.068***	**-0.100*****	**0.068***
	(0.092)	(0.329)	**(0.092)**	**(0.418)**	**(0.092)**	**(0.418)**
36-45	**-0.064*****	**0.035***	**-0.064*****	0.029	**-0.064*****	0.029
	(0.061)	**(0.215)**	**(0.061)**	(0.280)	**(0.061)**	(0.280)
56-65	**0.040***	**-0.062*****	**0.043***	**-0.069*****	**0.042***	**-0.069*****
	(0.063)	**(0.222)**	**(0.063)**	**(0.286)**	**(0.063)**	**(0.286)**
66-75	0.041	**-0.045***	0.043	-0.039	0.042	-0.040
	(0.108)	**(0.381)**	(0.108)	(0.492)	(0.108)	(0.492)
75+	0.015	-0.021	0.015	-0.017	0.015	-0.017

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
	(0.148)	(0.531)	(0.148)	(0.674)	(0.148)	(0.674)
University-level qualification	**-0.084***	0.009	**-0.084***	0.015	**-0.086***	0.014
	(0.111)	(0.341)	**(0.111)**	(0.502)	**(0.111)**	(0.502)
In a relationship	**0.104*****	**-0.045****	**0.102*****	-0.031	**0.105*****	-0.030
	(0.052)	**(0.182)**	**(0.052)**	(0.237)	**(0.052)**	(0.237)
Living with children	-0.019	-0.012	-0.020	-0.029	-0.019	-0.029
	(0.052)	(0.178)	(0.052)	(0.235)	(0.052)	(0.235)
Annual household income	-0.009	0.001	-0.009	-0.007	-0.009	-0.007
	(0.020)	(0.075)	(0.020)	(0.086)	(0.020)	(0.086)
Health condition	**-0.116*****	**0.133*****	**-0.116*****	**0.135*****	**-0.115*****	**0.135*****
	(0.044)	**(0.153)**	**(0.044)**	**(0.196)**	**(0.044)**	**(0.196)**
Like neighbourhood	**0.043*****	**-0.019***	**0.043*****	-0.016	**0.043*****	-0.016
	(0.047)	**(0.166)**	**(0.047)**	(0.212)	**(0.047)**	(0.212)
Employment status (reference: employed)						
Unemployed	**-0.055*****	**0.050*****	**-0.056*****	**0.050*****	**-0.055*****	**0.050*****
	(0.071)	**(0.250)**	**(0.071)**	**(0.323)**	**(0.071)**	**(0.323)**
Retired	0.033	**-0.039***	0.032	-0.037	0.033	-0.036
	(0.075)	**(0.275)**	(0.075)	(0.342)	(0.075)	(0.342)
Caring for family	0.018	0.009	0.018	0.017	0.018	0.017
	(0.071)	(0.256)	(0.071)	(0.319)	(0.071)	(0.319)
In training	-0.003	-0.012	-0.004	-0.030	-0.004	-0.030
	(0.083)	(0.286)	(0.083)	(0.369)	(0.083)	(0.369)
Other	**-0.021***	0.002	**-0.021***	0.009	**-0.021***	0.009
	(0.151)	(0.632)	**(0.151)**	(0.675)	**(0.151)**	(0.675)
House type (reference category: detached)						
Semi-detached	**-0.056***	-0.011	**-0.058***	0.001	**-0.057***	0.002
	(0.076)	(0.277)	**(0.076)**	(0.343)	**(0.076)**	(0.344)
Terraced	-0.042	-0.023	-0.044	-0.006	-0.045	-0.006
	(0.082)	(0.294)	(0.082)	(0.369)	(0.082)	(0.369)
Flat	-0.032	-0.004	-0.023	-0.013	-0.022	-0.013
	(0.088)	(0.317)	(0.088)	(0.395)	(0.088)	(0.395)
Other	**-0.033****	0.009	**-0.030***	0.016	**-0.031***	0.015
	(0.133)	(0.484)	**(0.133)**	(0.576)	**(0.133)**	(0.576)
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.017	**0.027***	-0.016	**0.035****	-0.017	**0.035***
	(0.064)	**(0.225)**	(0.064)	**(0.293)**	(0.064)	**(0.293)**
3 $\geq$ rooms per person	0.006	**-0.031***	0.009	-0.017	0.008	-0.018
	(0.053)	**(0.185)**	(0.053)	(0.240)	(0.053)	(0.240)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Life satisfaction	GHQ	Life satisfaction	GHQ	Life satisfaction	GHQ
Commuting time (reference category: None)						
< 15 mins	0.007 (0.059)	-0.013 (0.211)	0.007 (0.059)	-0.012 (0.263)	0.007 (0.059)	-0.012 (0.263)
16-30 mins	0.029 (0.058)	**-0.031*** **(0.209)**	0.028 (0.057)	**-0.045*** **(0.257)**	0.029 (0.057)	**-0.045*** **(0.257)**
31-50 mins	0.028 (0.062)	-0.026 (0.224)	0.027 (0.062)	-0.019 (0.275)	0.028 (0.062)	-0.019 (0.275)
> 50 mins	0.025 (0.062)	-0.005 (0.226)	0.023 (0.062)	-0.002 (0.276)	0.024 (0.062)	-0.002 (0.276)
Other						
Wave	**-0.048**** **(0.005)**	**0.064***** **(0.017)**	**-0.048**** **(0.005)**	**0.038**** **(0.022)**	**-0.047**** **(0.005)**	**0.038**** **(0.022)**

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

GHQ

When we observe the alternative measure of subjective well-being, the GHQ score, we find there to be the opposite effect on living within a 1km walk of a SINC (b=0.501, p=0.015). Remember that positive coefficients for the GHQ analysis indicate lower levels of mental health. This suggests that living close to a SINC is strongly associated with lower levels of well-being. In other words, living within 1km of a SINC reduces an individual's well-being by 0.501 on a scale of 0 to 36. Using standardised coefficients, the effect size of living within 1km of a SINC (β=0.043) is comparable to the negative effect of being unemployed (β=0.050) and the positive effect size of being in a relationship (β=-0.045).

4.4.2 Access to private open space

Life satisfaction

In model 2 we find that access to private open space is strongly and positively associated with higher levels of life satisfaction (b=0.180, p<0.001). We find that having access to a garden or terrace is related to a 0.180 increase in life satisfaction on a 1 to 7 scale. Using standardised coefficients, we find that having access to private space has a similar effect size to having access to SINCs (model 1). In fact, when we compare standardised coefficients, the effect size is comparable (public: β=0.043, private: β=0.049). We also find the effect size is half that of being in a relationship (β=0.102), or similar to that negative effect size of being unemployed, when compared to being employed (β=-0.056).

GHQ

We find that access to private open space is also strongly and positively associated with lower levels of mental distress (b=-0.687, p=0.002). We find that having access to private open space is related to a 0.687 decrease in mental distress on a scale of 0 to 36. Using standardised coefficients, we find that having access to a garden or terrace has the same effect size as that found for access to SINCs (model 2). However, despite the effects sizes being the same, the direction is different (public: β=0.043, private: β=-0.043). We also find that it is comparable to the negative effect of being unemployed (β=0.050) and a third of the negative effect size of having a health condition that limits work/activity (β=0.135).

Interaction between access to SINCs and private open space

Results of a Spearman correlation test find no correlation between access to SINCs and access to private open space (r=-0.020, p=0.048; Table 4.7). 38.6% of observations in the study relate to individuals who have access to both SINCs and private open space. To explore if access to a private open space (e.g. a domestic garden or terrace) affects the relationship between life satisfaction and access to public natural environments, we include access to private open space into the model (model 5). We find access to a garden/terrace is strongly and positively related to life satisfaction (b=0.182, p<0.001). This means that having access to private open space is associated with an increase of 0.182 in life satisfaction on a 1 to 7 scale. The addition of this variable does not largely change the effect size or significance of living within 1km of a SINC (b=0.120, p=0.042).

Table 4.7. Cross-tabulation of access to SINCs and access to private open space.

Access to SINCs	Access to private space	Number of observations	Percentage of all observations (%)
0	0	396	2.53
0	1	2804	17.88
1	0	970	6.19
1	1	6053	38.60
0	(missing)	1801	11.48
1	(missing)	3658	23.33

We include an interaction term into model 5 between proximity to a SINC and having access to a private open space, and this term is not significant (b=-0.064, p=0.508). Therefore, this suggests that while access to a private garden/terrace is important for life satisfaction, it does not moderate the positive well-being effects of close proximity to good quality public natural environments. In fact, when we compare standardised coefficients again, the effect size is comparable (public: β=0.044, private: β=0.049), demonstrating two significant different and direct ways that natural environments are associated with higher levels of life satisfaction (Figure 4.5). The relative effect size of other determinants of well-being can also be clearly seen, with comparable effect sizes of being aged 56-65 (reference category being aged 46-55), being in a relationship (reference category being single), not having a health condition that limits your ability to work and being unemployed (reference category being employed).

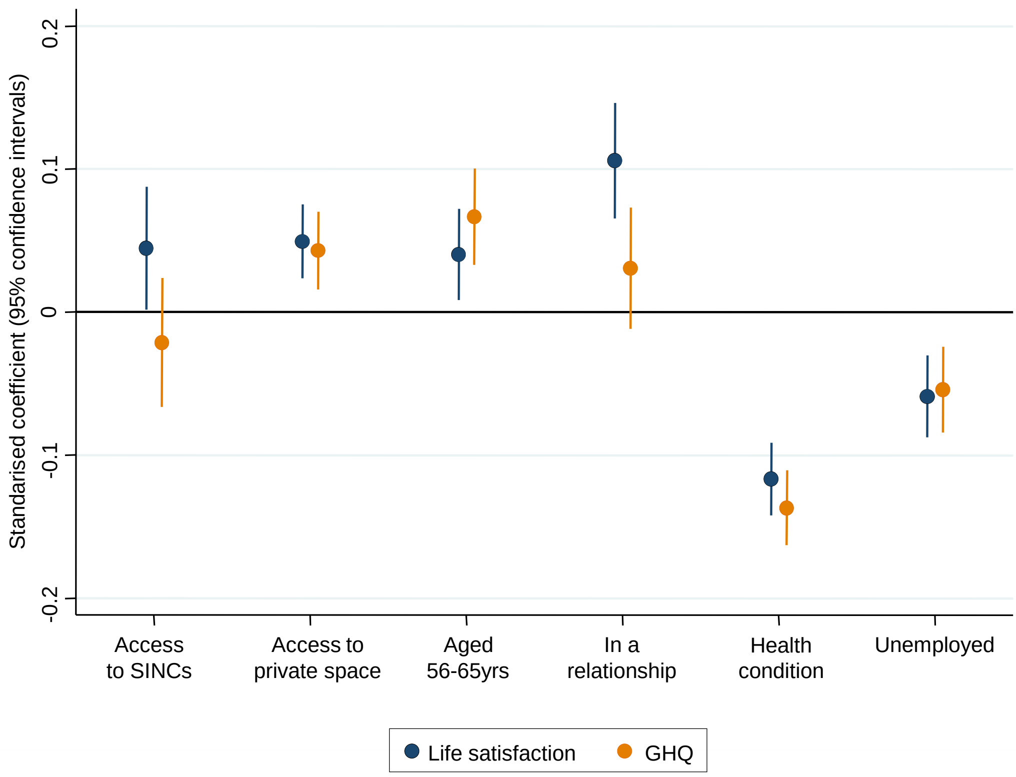

Figure 4.5. Standardised coefficients (models 5 and 6), showing the comparative effect sizes between access to SINCs, access to private open space, and other covariates in both the life satisfaction and GHQ models. The GHQ scale has been inverted here so that positive coefficients reflect better mental health. The category 'Aged 56-65yrs' shows the effect size when the reference category is 'Aged 46-55yrs, and similarly with 'Unemployed', the reference category is 'Employed'.

When we include having access to a garden/terrace (model 6), we find that having access to private open space is related to an improvement of mental health by 0.683 on a scale of 0 to 36 (b=-0.683, p=0.002). The addition of this variable in model 6 reduces the effect size of living within a 1km walk of a SINC, and the relationship is now no longer significant (b=0.248, p=0.353). When we include an interaction term between access to a SINC and access to a private garden/terrace, we find that it is not significant (b=0.398, p=0.373). Therefore, access to a private open space does not appear to moderate the negative relationship found between mental health and access to SINCs. This suggests that the positive significant relationship found between mental health and living within a 1km walk of a SINC is spurious, given that it is susceptible to change with the addition of variables. It is likely then that access to private open space is more important for mental health benefits than proximity to good quality public natural environments.

4.4.3 Access to POS

To test whether the quality of a public open space affects the relationship between well-being and residential proximity to a natural space, we conduct the above analysis replacing access to a SINC with access to each of the four categories of green/blue public POS (local, district, metropolitan and regional). We wanted to see if we find the same relationships as that found in the analysis with proximity to SINCs. We only find 1 significant relationship in this analysis: proximity to regional POSs and mental health (

Table 4.8, model 8d; b=-0.676, p=0.015). This suggests that living within an 8km walk of a regional POS is associated with a 0.676 improvement in mental health on a scale of 0 to 36. We did not find any other significant results. This suggests that the ecological quality of a public natural space is important to the well-being benefits gained from living in close proximity to it, and not just its presence.

When we include access to private open space in the analysis (models 9 and 10), we do not find any significant relationships between both well-being measures and all of the POS categories. We find that by including access to private space, the one significant relationship between regional POS and the GHQ is no longer significant, and the effect size is small (model 10d; b=-0.062, p=0.861). We also find in this analysis, the coefficient for having access to a private open space is positive for life satisfaction and negative for the GHQ (therefore both indicating a beneficial relationship for well-being). Using standardised coefficients (Table 4.9

Table 4.8), we can see that the effect size for access to a private open space is approximately twice the size as that of access to POS in all models. These findings suggest that access to private open space is more important for subjective well-being than access to public natural spaces.

Table 4.8. Public open space regression model results with unstandardised coefficients.

	Model 7	Model 8	Model 9	Model 10
	Life satisfaction	GHQ	Life satisfaction	GHQ
Not within AoD to local POSs	0.048	-0.054	0.048	-0.240
	(0.048)	(0.170)	(0.048)	(0.219)
Access to private open space	-	-	**0.181*****	**-0.689****
	-	-	**(0.049)**	**(0.221)**
Not within AoD to district POSs	0.066	0.182	0.073	0.327
	(0.052)	(0.183)	(0.052)	(0.235)
Access to private open space	-	-	**0.183*****	**-0.675****
	-	-	**(0.049)**	**(0.221)**
Not within AoD to metropolitan POSs	-0.093	0.227	-0.085	0.356
	(0.070)	(0.242)	(0.070)	(0.321)
Access to private open space	-	-	**0.179*****	**-0.678****
	-	-	**(0.049)**	**(0.221)**
Not within AoD to regional POSs	0.002	**-0.676***	0.006	-0.062
	(0.077)	**(0.279)**	(0.077)	(0.354)
Access to private open space	-	-	**0.181*****	**-0.688****
	-	-	**(0.049)**	**(0.221)**

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

Table 4.9. Public open space regression model results with standardised coefficients.

	Model 5	Model 6	Model 7	Model 8
	Life satisfaction	GHQ	Life satisfaction	GHQ
Not within AoD to local POSs	0.019	-0.005	0.019	-0.022
	(0.048)	(0.170)	(0.048)	(0.219)
Access to private open space	-	-	**0.049*****	**-0.043****
	-	-	**(0.049)**	**(0.221)**
Not within AoD to district POSs	0.026	0.017	0.029	0.030
	(0.052)	(0.183)	(0.052)	(0.235)
Access to private open space	-	-	**0.049*****	**-0.042****
	-	-	**(0.049)**	**(0.221)**
Not within AoD to metropolitan POSs	-0.029	0.017	-0.027	0.026
	(0.070)	(0.242)	(0.070)	(0.321)
Access to private open space	-	-	**0.048*****	**-0.042****

	-	-	**(0.049)**	**(0.221)**
Not within AoD to regional POSs	0.001 (0.077)	**-0.062*** **(0.279)**	0.003 (0.077)	-0.006 (0.354)
Access to private open space	- -	- -	**0.049***** **(0.049)**	**-0.043**** **(0.221)**

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

4.4.4 Sample descriptive statistics

The relationship between our measures of subjective well-being (life satisfaction and the GHQ) and our suite of control variables are consistent with current literature. In models 5 and 6, we find that higher levels of life satisfaction and lower scores of the GHQ are positively associated with being aged between 56-65 years old when compared to being 46-55 years old (life satisfaction: b=0.155,p=0.013); GHQ: b=-1.108, p<0.001). They are negatively associated with having a health condition that limits one's ability to work (life satisfaction: b=-0.396, p<0.001); GHQ: b=2.009, p<0.001), and being unemployed (when compared to being employed; life satisfaction: b=-0.287, p<0.001; GHQ: b=1.144, p<0.001). We also find a significant association between the wave variable and both life satisfaction and the GHQ (b=-0.015, p=0.001, and b=0.057, p=0.009 respectively), indicating a reduction in subjective wellbeing through time.

Several variables are significantly associated with only one of either life satisfaction or the GHQ. We find that being in a relationship is positively related to life satisfaction (b=0.268, p<0.001), and negatively related to living in a semi-detached house or "other" housing type category when compared to living in a detached house (b=-0.164, p=0.032, and b=-0.321, p=0.016 respectively). Interestingly, we find that holding a university-level degree is negatively associated with life satisfaction (b=-0.235, p=0.033). Lower GHQ scores are positively associated with having a commute length of 16-30 minutes when compared to having no commute (b=-0.649, p=0.012), and are negatively associated with living in a house with less than 1 room per person, when compared to that of between 1-3 rooms per person (b=0.753, p=0.010).

4.4.5 Sensitivity testing

We conducted the analysis again, this time using LSOA population-weighted centroids instead of postcode unit centroids. This allowed us to test whether analysis at the LSOA-level achieves the same relationships. LSOAs are frequently used as a neighbourhood boundary to investigate relationships between residential natural environments and health and well-being. We did not find any significant relationships between access to SINCs and life satisfaction or GHQ in this analysis (full results available upon request). We did however still find the positive and significant associations between access to private open space and both life satisfaction and the GHQ. Given that the geographical location was only used to identify the proximity to SINCs and POSs, this suggests that conducting this analysis at the more generalised LSOA-level is not sufficient at capturing an individual's residential exposure to public natural spaces.

We also investigated the relationship between life satisfaction and the GHQ, and to establish if it is worthwhile to use these two measures of subjective well-being when examining the association with access to public and private open space. Following White et al. (2013) we included the GHQ as a covariate in the life satisfaction analysis (model 5), and likewise with life satisfaction into the GHQ analysis (model 6). We found that access to SINCs was still a significant predictor of life satisfaction when controlling for GHQ (b=0.120, p=0.026), as was access to private open space (b=0.122, p=0.007). When we controlled for life satisfaction, access to SINCs was still not a significant predictor of GHQ (b=0.235, p=0.363), and access to private open space remained only a marginally significant predictor of GHQ (b=-0.382, p=0.075). Full models are available upon request.

4.5 Discussion

Our study aimed to understand the importance of quality of the natural environment when exploring the relationship between subjective well-being and residential proximity to public green and blue spaces in London. We also aimed to understand if private open space was important for well-being, and how having access to private space affects the relationship between public open space and well-being. We used a large sample size of individuals, two measures of subjective well-being, and a suite of control variables. We used a proximity measure based on walking distance along actual known routes and access points, and employed longitudinal well-being data and fixed effects regression allowing us to address unobserved time-invariant heterogeneity in the sample. We also used two levels of residential location to examine the effect of spatial error in our exposure estimation.

4.5.1 Quality of public natural spaces

Our results suggest that living within a 1km walk of a high quality public natural site (SINCs) is beneficial for well-being, when measured by life satisfaction. This relationship is not significant when repeating the analysis using all public green and blue spaces. This suggests that the quality of the natural environment, specifically its importance for nature conservation, is an important factor when considering the well-being benefits gained from public natural spaces. This supports a small but growing body of literature that finds indicators of green/blue space quality are strong predictors of health and well-being (Brindley *et al.* 2019; Wood *et al.* 2018; Wyles *et al.* 2019). Despite the effect size being relatively small on the life satisfaction Likert scale, it is comparable to that of other major determinants of well-being controlled for in the analysis, such as being in a relationship and unemployment. Additionally, the positive effect size for one individual is greatly amplified when considering the number of people who are able to access to SINC. The aggregated community-level benefits of access to SINCs may actually be quite significant (White *et al.* 2013b, 2013a).

There are a number of reasons why this might be. We capture sites that have been considered to be important for nature conservation; SINCs are sites of biological significance and therefore support important biodiversity. Previous studies suggest that increased biodiversity is related to higher levels of well-being (Cameron *et al.* 2020). More biodiverse environments may provide more opportunities for psychological and physiological restoration. For example, environments that provide opportunities for 'soft' distraction, such as noticing habitats or birds, as opposed to 'hard' distraction such as car noise and traffic lights, have been associated with greater cognitive functioning and lower heart rates. Alternatively, it might be that places of higher or important biodiversity, particularly in urban areas, are seen as special, rare or different (Cameron 2020). This might be particularly important in highly urbanised areas, where opportunities to connect to nature are few (Carrus *et al.* 2015).

The literature relating to the relationship between well-being and biodiversity finds results that are contradictory and unclear. This might be due to the variety of biodiversity measures used, or our lack of understanding of how exactly humans perceive and experience biodiversity (Lovell *et al.* 2014; Pett *et al.* 2016). Previous studies measure biodiversity in a number of ways, by using objective scores of species richness (Cameron *et al.* 2020; Luck *et al.* 2011), habitat diversity (Cameron *et al.* 2020), vegetation cover (Dallimer *et al.* 2012), NDVI standard deviation (Mavoa *et al.* 2019a) or protected area status (Wheeler *et al.* 2015; Wyles *et al.* 2019), and subjective scores such as perceived biodiversity (Dallimer *et al.* 2012). Using the categorisation of SINCs, instead of alternative metrics for biodiversity, may be useful, as it avoids some of the issues concerning the use of other biodiversity metrics. For example, objective measures of biodiversity (i.e. which species to include (all, rare species only, relatively well quantifiable species such as birds) and which type of biodiversity to measure (e.g. richness or abundance), subjective measures such as perceived biodiversity (which may or may not capture indirect benefits of exposure to biodiversity), and indices such as NDVI (which only measure "greenness"). Sites may be considered important for nature conservation because they contain protected habitat, which in turn supports important or higher levels of biodiversity. These are both difficult biodiversity concepts to capture in biodiversity metrics, and reflect the likely multi-faceted ways that humans might experience biodiversity. Using a site categorisation that encapsulates several biodiversity or quality flags may be a better proxy for biodiversity when attempting to understand the relationship between nature and well-being.

4.5.2 Access to private open space

Our results suggest that access to a private open space is beneficial for well-being in London, as measured by both life satisfaction and the GHQ. Access to a garden or terrace is associated with higher levels of both life satisfaction and lower levels of mental distress. This result suggests the well-being importance of private open space, supporting previous research in this field (de Bell *et al.* 2020b; de Vries *et al.* 2003; Dennis & James 2017; Mavoa *et al.* 2019a).

The well-being importance of having access to a domestic garden or terrace might be explained in a number of ways. Properties with access to domestic space tend to be in neighbourhoods that are considered more desirable, although we try to account for this by including an individual's neighbourhood satisfaction and deprivation indices for each LSOA. Well-being benefits may be achieved by allowing individuals private opportunities to experience and interact with nature and outdoor activities. Activities such as gardening and bird watching for example have been linked to improved well-being (Cox & Gaston 2016). Alternatively, well-being benefits from gardens/terraces may also be achieved simply from their presence. Benefits from gardens could be achieved passively and therefore do not require visits or time spent within them (Coldwell & Evans 2018). Certainly there is a large body of evidence to show that private green spaces act as therapeutic landscapes (van den Berg *et al.* 2010b) and that green views from buildings provide restorative benefits to individuals (Kaplan 2001). Private spaces may also be associated with feelings of security and ownership (de Bell *et al.* 2020b).

4.5.3 Access to public and private natural space

We then examined if having access to a private open space moderates the relationship between higher levels of well-being and access to high quality public open spaces. In our life satisfaction analysis, having access to a private garden or terrace and living within a 1km walk of high quality public natural sites are both significant for well-being, with comparable effect sizes. This suggests that access to both private and high quality public open spaces is important for the life satisfaction of residents in London. In other words, the proximity to private and public green/blue spaces both have direct and separate positive effects on life satisfaction. This finding supports the small current body of literature which finds both public and private natural space improves well-being.

Our results suggest that, in the case of mental distress, access to a private garden or terrace is more important in providing well-being benefits than proximity to good quality public open space. Surprisingly, we did not find a relationship between access to SINCs and mental health, as measured by the GHQ. We did however find a positive and significant association between access to private open space and mental health. We suggest that the initial negative association found between access to SINCs and the GHQ was spurious. In later models, we find the association disappears altogether. This finding contradicts that of our other measure of well-being, life satisfaction, and perhaps demonstrates the different aspects of subjective well-being that these two measures capture. Indeed this finding supports that of other research that finds nature exposure has a stronger effect on positive rather than negative emotions (McMahan & Estes 2015; White *et al.* 2017).

4.5.4 The importance of spatial scale

We also find that the spatial accuracy of the residential address is important when measuring how an individual is exposed to public spaces. These relationships were found when using a postcode unit centroid, which is highly accurate to an individual's residential location. We did not find these relationships when we conducted the same analysis at the less spatially resolved LSOA-level (population–weighted centroid). This was surprising, given that LSOAs are generally small in London (mean size is 3.3 km^2, the mean for England is 4 km^2). This finding suggests that there are important differences in walking time and access to public open spaces across different locations within an LSOA, and that the population-weighted centroid location is not necessarily a useful proxy for residential location. The population-weighted centroid of an LSOA is an aggregation of all the population-weighted centroids of the underlying output areas (OAs) that make up an LSOA. Therefore, in reality there will be several locations within an LSOA which represent a residential node (Higgs & Langford 2009).

This is an important finding as it offers a possible explanation for why we might find mixed results from other analyses using 'small' geographical areas (Wheeler *et al.* 2015). This 'exposure misclassification' is very common as a source of bias in environmental epidemiology, termed 'information bias' or 'ecological bias', and usually leads to bias toward the null (Morgenstern & Thomas 1993). Our findings are consistent with this, with potentially increased levels of exposure misclassification when estimating at the LSOA-level, highlighting the importance of using accurate location data when estimating the relationship between human well-being and the natural environment (Nuckols *et al.* 2004).

4.5.6 Implications, limitations, and future work

Considerations and future work

The relationship between human well-being and the natural environment is complex, and here we have attempted to address some of the key issues with current research to date. Using longitudinal data pertaining to individuals is important, allowing us to control for time-invariant heterogeneity, and is an important improvement on cross-sectional analyses. However, there will always be other sources of bias due to unaccounted error in the model. The R^2 values of all our models are between 0.03-0.05. This suggests that there is still a large amount of variance that is being unaccounted for in our models, and may be explained by time-varying omitted variables in our model specifications. However, this is extremely common and reflects the complexity in capturing the determinants of well-being in humans (White *et al.* 2013b, 2013a). Future work could employ analytical techniques which allow longitudinal and experimental designs, or quasi-experimental designs such as instrumental variables regression, although it is difficult to find a suitable instrument that is related to proximity to open space but not to well-being. Furthermore, it is possible that the relationship between open spaces and well-being varies between people and places (Giles-Corti *et al.* 2008; Houlden *et al.* 2019a, 2019b; Labib *et al.* 2020b). Future work could use spatial regression techniques that allow model parameters to vary over space, such as Geographically Weighted Regression (Houlden *et al.* 2019a).

We use data modelled by GiGL to identify areas of deficiency to public open spaces and sites of importance for nature conservation. These were based on highly spatially detailed and up-to-date information concerning green and blue spaces in London. However, these data only relates to one situation in time, open space time-series datasets were not available. This is common and persistent limitation of environmental data. The hard boundary of our Greater London data may exclude the calculation of proximity to natural sites outside of the city, but this data was not available in this analysis. The POS and SINC datasets are also comprised of both green and blue spaces; we did not examine the potentially different ways that green and blue spaces may affect subjective well-being (Garrett *et al.* 2019b; Pasanen *et al.* 2019). We assume a site that is categorised as a SINC reflects a level of environmental quality, as it has been agreed by a local expert panel. Of course, future research could couple this categorisation with alternative environmental data, such as biodiversity records, and additional quality flags, such as cleanliness.

In our sample, we find that the overwhelming majority of individuals have access to private open space. However, recent research revealed that 1 in 5 Londoners do not have access to a private garden, which is higher than the national average at 1 in 8 for British households (Office for National Statistics 2020b). The ONS also report clear inequities in access to private and public open space. For example, 37% of black people in Britain have no access to outdoor space at home, compared to just 10% of white people, and people in "semi-skilled" and "unskilled" manual occupations, casual workers and those who are unemployed were almost three times as likely to have no garden compared to those in managerial, administrative, or professional jobs (ONS 2020). Lynn and Borkowska, (2018) analysed attrition and representativeness across the waves of the BHPS and despite finding relatively low levels of attrition, they find that attrition was greater amongst younger age groups, men, black people and participants on lower incomes. This reported underrepresentation of certain demographics in the BHPS over time may be a factor in explaining our findings. Important future work should explore this differentiated exposure to private open space and examine the impact this might have on the relationship with well-being.

Additionally, we do not know anything more about the characteristics and qualities of this open space, whether it is a garden or a terrace, and moreover the ecological qualities of it. Indeed recent research has suggested different well-being effects between domestic gardens and private open space, as well as the difference between truly private and shared private communal space (de Bell *et al.* 2020b). No further questions were asked relating to this survey item. An important further area of research would be to explore how different characteristics of private open space, such as ownership, land cover and biodiversity, affect the positive relationship with well-being.

We use a series of datasets calculated using a proximity measure based on walking distance along actual known routes and access points. This is a more sophisticated approach to, for example, using presence/proportion metrics within a neighbourhood or buffer. This is because it captures a more realistic measure to how an individual moves in space. Although residential proximity or access to natural environments does not capture use or 'exposure' to a site, nor does it capture exposure dose, nor the preferences of the individual and activities conducted while there, it is related to direct use of natural spaces. For example, residential proximity to an urban green space has been shown to be associated with an increased number of visits to the site (Ayala-Azcárraga *et al.* 2019; Grahn & Stigsdotter 2003).

Although availability and access to natural environmental have not been found to sufficiently explain use (Cox *et al.* 2017), there is also reason to accept that an individual does not necessarily have to use a site to gain well-being benefits from it. We do accept however that an individual may be gaining well-being benefits from the natural environment by visiting sites outside of their residential surroundings (White *et al.* 2019). Additionally, individuals in the survey moved out of London and therefore we were not able to track the effects of changes in their exposure to the natural environment beyond this point. However, this will always be an issue in any panel data, for example if an individual emigrates.

We cannot be sure if our findings found here for London will apply more broadly to other large urban areas similar to London, such as other English cities and that across the Global North. London is considered approximately comparable to Rome, Madrid and Rio de Janeiro, and above New York and Berlin when ranked by public greenspace percentage area per capita (World Cities Culture Forum 2017). However, how it might translate to rural areas is unknown. Evidence shows those in urban areas gain fewer benefits from the environment than those in rural areas (Lapointe *et al.* 2020), and that Londoners are more likely to use greenspaces to meet with friends, and less likely for dog-walking, than those outside of London (Fields in Trust 2018). Selection bias may also be that those seeking to live in the capital are those who are least concerned about exposure to the natural environment, and therefore least affected in terms of their well-being. It is also not clear if these findings would apply in other parts of the world, for example those with vastly different levels of biodiversity.

Implications and significance

It is clear that improving and maintaining the biological quality of London's public and private, spaces will be beneficial for the subjective well-being of residents. Higher levels of life satisfaction are also associated with lower levels of physical and mental health conditions, as well as improved productivity in the workplace. This represents a huge potential national economic gain, and the benefits of focussing policies towards improving well-being have been widely recognised (Environment Agency 2020). The key mechanisms for improving the quality of London's natural spaces include planning legislation and funding for conservation. Improving the biodiversity and ecological quality of public green and blue spaces in London should be a priority, as well as improving access. Despite this being highlighted as a priority in The London Plan, SINCs are coming under increasing pressure due to demand for land from development, and some SINCs have been developed or encroached on (London Wildlife Trust 2015). Our findings suggest that the SINCs network is an important part of the capital's land use infrastructure for individual well-being in the city.

The well-being importance found here of having access to a private garden or terrace in London is significant. Recent work has suggested that London's gardens are getting smaller and greyer, a pattern identified in other urban areas around the world (Haaland & van den Bosch 2015). Smith et al., (2011) used aerial photography to measure change in vegetation structure in domestic gardens in London between 1998 and 2008. They found that hard garden surfaces increased by 26% over the study period, and garden buildings increased from 1,800ha to 2,800ha. This represents a mean of 11m^2 vegetation lost from an average back garden (6m^2 from front gardens) over 11 years, reducing London's average garden per dwelling by 8.5% (from 200m^2 to 183m^2). Despite this move from green to grey being driven by individual (or household) choice, removing the greenness from private gardens has the potential to reduce the overall well-being benefits experienced by individuals. Garden space also represents 24% of Greater London's total area (comparable to that in another British city, 23% in Sheffield), and provides a significant land area that maintains connectivity for biodiversity across the city's private and public natural environments (Davies *et al.* 2009). It is likely that, like public spaces, the biodiversity of private gardens is a key factor in delivering well-being benefits to humans.

We use the specific walking distances as detailed in The Mayor of London's The London Plan, a planning guidance document detailing the intentions for London' green and blue spaces, amongst other land uses (Greater London Authority 2016). The walking distances are designed as the maximum distance as individual should live from a natural public space in London, and are based on the assumption that individuals will travel further for open spaces that are larger and contain more facilities. Alternative recommendations regarding individuals' exposure to the natural environment exist in the UK. For example, through the Accessible Natural Greenspace Standard (ANGSt), the UK Government recommends that individuals should be provided with an accessible, natural greenspace of at least 2 ha in size, within a 300m walk of their home (Natural England 2010). However, the ANGSt also highlights the importance of locally determined distances that account for localised contexts, and as such there exist a range of guidance recommendations across the country. It is clear there are key evidence gaps in the understanding of how exposure mode affects the relationship between the natural environment and individual well-being measures (Defra 2017).

Furthermore the London Plan predicts that 10% of London's residents have a disability or sensory impairment, and states that "ensuring London and its infrastructure is accessible and inclusive will have to be a key theme of the new London Plan" (Greater London Authority 2016). London also has a younger population than the rest of England and Wales, and is predicted to continue to diversify in terms of ethnic communities. Therefore, by improving the provision and quality of the city's public and private green and blue spaces, the city is addressing the health and well-being needs of several demographics who have previously been found to have disproportionately poor access to public green and blue spaces (Roe *et al.* 2016).

Conclusions

Our study finds that proximity to generic public open spaces does not provide well-being benefits to residents in London. However, residential proximity to high quality publicly accessible sites (sites considered important for nature conservation) does. This highlights the importance of including the heterogeneous nature of urban natural environments in analyses, particularly the designation based on biodiversity importance, of a site. Moreover, we find that having access to a private garden or terrace is also beneficial for well-being, and that it has a separate and direct effect to that of public natural sites. Therefore, both private and high quality public natural spaces provide well-being benefits in London.

We find that the relationship between well-being and public and private natural environment differs with the metric of well-being being observed. Private open space in London is important for both life satisfaction and mental health, but high quality public open space is important for life satisfaction only. Therefore, it is important to include multi-dimensional measures of well-being when exploring this relationship.

Our paper contributes to a small body of research that examines how ecological quality affects the relationship between human well-being and the natural environment. Future research should focus on the mechanisms that underpin the relationships we find, to enable informed recommendations for how public open spaces could be modified to enhance their potential to deliver well-being benefits. We also suggest that future work should account for spatial variations in the relationship between individual well-being and the natural environment, and also to examine the importance of the ecological quality of private urban natural spaces.

Chapter 5: Does wildlife make us happy? Investigating the relationship between biodiversity and subjective well-being

5.1 Abstract

There is increasing evidence that green- and bluespaces in urban areas are associated with better health and well-being for residents. However, little is known about how the biodiversity and habitat characteristics of open spaces contribute to well-being. We use fixed effects regression to explore the relationship between three subjective well-being measures (life satisfaction, mental health, and self-reported general health) and exposure to habitats and biodiversity. We use detailed habitat, species presence databases and Normalised Difference Vegetation Index (NDVI) layers to calculate environment metrics for Greater London. We use two different methods for capturing exposure: neighbourhood composition and distance-decay functions to open space sites (OSS). We find habitat diversity is not important for well-being, but certain habitat types are. The strongest evidence for a positive association is with Allotments, Herb-rich grassland and Still water, and for negative associations with several woodland types (Native and Non-native broadleaf woodland) and several semi-wet and wild types (e.g. Swamp, Intertidal and Saltmarsh). We find some association between biodiversity and subjective well-being, finding a positive significant relationship between self-reported general health and butterfly and bird species richness, and NDVI (mean and standard deviation). These relationships differ between population sample, well-being measure and exposure methods used. Our findings suggest the importance of habitat type and biodiversity for well-being, but not habitat diversity. Our findings are important for policymakers and conservation organisations who seek to better understand the link between biodiversity and human health and well-being, in order to better promote both.

5.2 Introduction

Urbanisation is described as one of the world's current major threats to health (World Health Organisation 2016). Despite urban populations benefitting from, generally, better economic prosperity, better sanitation, nutrition and health care (Dye 2008), city dwellers are more at risk from chronic, non-communicable and mental health conditions (Cox *et al.* 2017; Dye 2008; Lederbogen *et al.* 2011; Peen *et al.* 2010). For example, the growing incidence of conditions such as depression have been attributed to the modern urban environment (Hidaka 2012), and urban populations are more likely to experience mood and anxiety disorders than their rural counterparts (Peen *et al.* 2010).

There is increasing evidence that green- and bluespaces in urban areas are associated with better health and well-being for residents (Houlden *et al.* 2018; Taylor *et al.* 2018; Twohig-Bennett & Jones 2018). There is also evidence to suggest that the ecological quality or biodiversity of urban natural spaces is important, with more biodiverse environments related to higher levels of health and well-being (Cameron *et al.* 2020; Clark *et al.* 2014; Lovell *et al.* 2014; Luck *et al.* 2011). This has important implications for urban design and planning, as well as any future nature-based interventions or developments in urban areas. Recent research shows that despite urban areas being highly modified landscapes, urban green- and bluespaces can provide habitats for important biodiversity and play a key role in delivering a range of ecosystem services for urban populations (Angold *et al.* 2006; Aronson *et al.* 2017).

However, biodiversity is declining globally (Mace *et al.* 2018; Pimm *et al.* 2014). A recent report shows that global targets to halt this decline (the Aichi Biodiversity Targets) will not be fully met, in turn threatening the achievement of the Sustainable Development Goals (Secretariat of the Convention on Biological Diversity 2020). As urban areas are increasingly more crowded and polluted than rural areas (Dye 2008), there is less space for nature to thrive (Cox *et al.* 2018). In Europe, loss of urban greenspace due to infilling and redevelopment has been reported (Haaland & van den Bosch 2015), and urban densification has led to cities with higher population densities having lower greenspace per capita (Fuller & Gaston 2009). In England, urban greenspace reduced by 8% between 2001-2018, from 63% to 55% (Committee on Climate Change 2019). With over 60% of the global human population estimated to be living in urban environments by 2050 (World Health Organisation 2016), urban natural environments are likely to become increasingly under pressure due to demand for space, yet they represent a significant opportunity to provide health and well-being benefits to the growing population.

The recognition of the salutogenic benefits of the natural environment, particularly in urban areas, is reflected in the recent increase of broad global agreements to address the quality and provision of urban green- and bluespaces in relation to human health. For example, the UN Sustainable Development Goals aim for universal access to good quality and accessible greenspaces in cities by 2030 (United Nations 2017). The World Health Organisation's European Healthy Cities Network sets out a vision for physical environments that enable and drive health and well-being for all (World Health Organisation 2018). At a national level, one of the six key policy areas in the UK government's 25 year Environment Plan is to connect people to nature to improve health and well-being (HM Government 2018).

However, there is very little consistent information regarding how to implement these broad statements on nature provision, quality and exposure (Douglas *et al.* 2017; Hunter *et al.* 2019), and no guidance on how habitats and biodiversity fit into these statements. Urban green- and bluespaces provide habitats for species diversity, and contribute to the important network of patches and corridors that allow species to live and move around urban green infrastructure (Villaseñor & Escobar 2019). However, little is known about the biodiversity and habitat characteristics that contribute to human well-being. There have been recent calls for more research to identify how different attributes and measures of *quality* of green- and bluespaces are associated with specific health benefits (Akpinar *et al.* 2016; Hartig *et al.* 2014; Nieuwenhuijsen *et al.* 2017; Sandifer *et al.* 2015; van den Berg *et al.* 2015; Wheeler *et al.* 2015). However, hindering progress in this area is the fact that biodiversity data are difficult to obtain and integrate into health and well-being studies, and the interdisciplinary nature of the research area requires the involvement of a range of expertise, from public health experts, biomedical and social scientists, to ecologists, economists and land use planners (Sandifer *et al.* 2015).

It is well understood that biodiversity is important in underpinning key ecosystem services, such as the provision of food and shelter to support and sustain livelihoods (Millennium Ecosystem Assessment 2005). There is also some evidence to suggest that the biodiversity of urban natural environments is related to subjective measures of well-being, such as mental health and happiness. For example, positive relationships have been found between measures of well-being and bird species richness and habitat diversity (Cameron *et al.* 2020; Wood *et al.* 2018), and plant species richness (Lindemann-Matthies & Matthies 2018).

Particular habitat types have also been found to be important for well-being in urban areas. Positive associations have been found between subjective well-being measures and natural land cover categories, such as coastal, freshwater, woodland, grassland, and upland environments (Jarvis *et al.* 2020b; MacKerron & Mourato 2013; Wheeler *et al.* 2015; White *et al.* 2013c). Allotment use has been associated with greater levels of physical activity and well-being, especially in older age (van den Berg *et al.* 2010b). The habitats surrounding an individual's residence have also been found to be important for the health and well-being of its residents. Studies have demonstrated associations between mental health and freshwater habitats (Pasanen *et al.* 2019), and residential proximity to trees has been positively associated with self-reported health (Reid *et al.* 2017), lower prescription rates of antidepressants (Taylor *et al.* 2015), and psychological well-being (Wang *et al.* 2020).

Perhaps the closest study to ours is that conducted by Wheeler et al., (2015), using an ecological approach to assess the relationship between habitats and biodiversity in English LSOAs and individual well-being. They found a positive relationship between good self-reported general health (and a negative relationship with bad self-reported general health) and natural land cover types (broadleaf woodland, arable and horticulture, improved grassland, saltwater and coastal) and habitat diversity (Shannon's Diversity Index). They did not find any significant relationships with coniferous woodland, semi-natural grassland, mountain/heath/bog, or freshwater. Interestingly, they find a positive relationship with bird species richness but no negative relationship with bad self-reported general health.

Other studies also find mixed results. A study conducted in parks in Sheffield, UK found a positive relationship between psychological well-being and bird species richness, a negative relationship with plant richness, and no relationship at all with butterfly richness (Dallimer *et al.* 2012). Another study, also conducted in Sheffield, found plant species richness, and to a lesser extent bird species richness, to be related to at least two measures of well-being (Fuller *et al.* 2007). However butterfly species richness and tree canopy cover had no association with any well-being measures.

Furthermore, studies examining the relationship between neighbourhood biodiversity and well-being also find mixed results. Luck et al., (2011) found a positive relationship between vegetation cover and subjective wellbeing, but only a weak positive relationship with bird species richness and abundance. Taylor et al., (2018) found an association between general well-being and NDVI (mean and standard deviation, the latter as a proxy for biodiversity) in Australia but not for bird species richness, and the association only occurs in two of their four study cities.

A positive association between subjective well-being and *perceived* measures of biodiversity has also been found in studies of park visitors, such as with perceived height of trees and bird song (Ayala-Azcárraga *et al.* 2019), and perceived presence of wildlife (Garrett *et al.* 2019b). Certainly evidence suggests perceived species-richness is a suitable proxy for actual species-richness (Southon *et al.* 2018), but perceived biodiversity has also been found to better predict subjective well-being than objectively measured biodiversity (Dallimer *et al.* 2012; Schebella *et al.* 2019).

This has been termed the people-biodiversity paradox (Pett *et al.* 2016). This describes there being a mismatch between an individual's biodiversity preferences and how they relate to their well-being, and people's ability to accurately perceive actual biodiversity levels. For example, higher levels of well-being benefit have been reported from species groups hypothesised to be charismatic (birds, flowering plants and butterflies), and less so from those perceived as less charismatic (beetles/bugs, brambles and nettles), and from respondents who report higher levels of biodiversity appreciation and value (Hoyle *et al.* 2019; McGinlay *et al.* 2017).

It is likely that the relationship between biodiversity and well-being is personally, socially, and culturally dependent (Pett *et al.* 2016), and that the beliefs and perceptions held by individuals will affect the well-being impacts of exposure to green- and bluespace (Marselle *et al.* 2015). For example, studies have found the relationship between biodiversity and well-being may be mediated by perceived restoration (Carrus *et al.* 2015; Marselle *et al.* 2015), nature connectedness (Cox *et al.* 2017), or eco-centricity (Southon *et al.* 2018). There are also socio-demographic influences, for example perceived naturalness was found to be related to participants' educational qualifications and gender (Hoyle *et al.* 2019).

There certainly is no clear conclusion to be drawn from the current well-being and biodiversity literature, further research is needed to better understand if biodiversity is beneficial for individuals. This requires an understanding of what facets of biodiversity might be important (e.g. specific species/taxa/habitats, overall diversity). It is reasonable to suggest that natural environments with higher levels of biodiversity should provide more health benefits to humans than those of lower biodiversity levels but the evidence is not robust (Lovell *et al.* 2014). One suggestion is that higher biodiversity levels indicate a more robust ecosystem, providing ecosystem services that improve well-being, such as food provisioning, or recreational value (Aerts *et al.* 2018). Another is that more biodiverse environments provide increased opportunities for interacting with nature, which has restorative psychological and physiological benefits (see Marselle, 2019 for a full review).

The different metrics and characteristics of biodiversity yield differing results and this relationship needs further research. Moreover, research indicates that while urban sites that support higher levels of habitat diversity and biodiversity are likely to be larger, less fragmented and considered more 'wild' (Ayala-Azcárraga *et al.* 2019), this urban structure in fact limits human access and use, and therefore the potential for individuals to gain well-being benefits from them (Jennings *et al.* 2017). It is likely that biodiversity levels are affected by habitat types, so it is important to observe these two metrics separately. Gaining a better understanding of how habitats and biodiversity affect well-being will be important for informing future green- and bluespace planning.

Underpinning the question regarding which facets of biodiversity may or may not be important for health and well-being is another important consideration: how is biodiversity best measured? Biodiversity is defined by the Convention for Biological Diversity as "the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species, and of ecosystems" (United Nations 1994). Therefore, biodiversity is part of, but not completely, defined as nature (Sandifer *et al.* 2015). There are generally three types of habitat and biodiversity data used in the health and well-being literature, field surveys, remotely sensed data, and citizen science data. Field surveys are commonly conducted in a sample of green- and bluespaces specifically for the study (e.g. Fuller et al., 2007; Wood et al., 2018; Cameron et al., 2020). These can be very insightful datasets but are relatively small-scale, and are largely unable to be reused in future studies. Remotely sensed data has the benefit of being available for relatively large land areas, with consistent characterisation protocols. Land use land cover datasets, such as the European CORINE database or the UK Land Cover Map product, are produced from remotely sensed imagery, and provide a consistent and large-scale product to then analyse (Akpinar 2016; Wheeler *et al.* 2015). Similarly, vegetation or 'greenness' indices can be derived from remote sensing imagery, such as the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). These have been used increasingly in health and well-being literature (e.g. Pereira et al., 2013; Crouse et al., 2017; Reid et al., 2018; Mavoa et al., 2019).

The third type is citizen science biodiversity and habitat monitoring data. This entails the involvement of both scientist and non-scientist individuals in data collection; volunteer and non-volunteer experts and interest groups in biological recording (Pocock *et al.* 2018), and it is relatively under-used in health and well-being literature. One such study using this type of data is Wheeler et al., (2015), who used bird species richness data from the BTO Bird Atlas 2007-2011 to explore the relationship between biodiversity and self-reported well-being at the LSOA-level.

The use of citizen science to examine trends in biodiversity is a diverse and rapidly expanding field (e.g. Pellissier et al., 2020). There is no doubt that citizen science databases have been hugely influential (Callaghan *et al.* 2019), however they remain relatively underused in the scientific literature (Theobald *et al.* 2015). In 2011, the value in the UK of volunteer monitoring of the environment was valued at around £50 million (Defra 2011). The use of citizen science data could play an important role in providing large-scale evidence to underpin policy (Hyder *et al.* 2015).

Citizen science databases have many potential benefits. These include collecting data at larger spatial and temporal scales than would be possible by scientists alone, filling in data gaps such as times of year, and cost-effectively collecting large volumes of data (McKinley *et al.* 2018). Data can also be collected at a higher spatial resolution and with a great level of detail than remotely sensed data. Despite the many known potential issues and biases found in this type of data (e.g. selection bias, pseudo-replication, spatial bias, species reporting bias), many databases ensure rigorous experimental design, quality control and assurance, and the use of accepted standard analytical and statistical techniques (McKinley *et al.* 2018).

NDVI has also been used as a proxy for biodiversity in ecological and biogeographical literature. Mean NDVI has been found to be associated with percentage tree cover and plant species richness (Brun *et al.* 2019; Levin *et al.* 2007), bird species richness (Bino *et al.* 2008; Taylor *et al.* 2018) and arthropod species richness (Turrini & Knop 2015). NDVI variation, measured by the NDVI standard deviation, has been found to be a good proxy of landscape heterogeneity and biodiversity (Gould 2000), positively correlated with plant species richness (Gould 2000; Levin *et al.* 2007; Oindo & Skidmore 2002), bird species richness (Bino *et al.* 2008; Culbert *et al.* 2012), and butterfly species richness (Seto *et al.* 2004). It has long been understood that a positive relationship exists between mean NDVI and net primary productivity, and therefore biodiversity, with the assumption that higher levels of productivity lead to higher levels of habitat and plant diversity and therefore higher levels of faunal diversity.

A handful of health and well-being studies have used NDVI (mean and variation) as an indicator for biodiversity (Mavoa *et al.* 2019a; Pearson *et al.* 2020; Pereira *et al.* 2012, 2013; Taylor *et al.* 2018), with mixed results. Mavoa et al., (2019) found positive relationships between subjective well-being and residential mean NDVI in Melbourne, Australia, but found no relationships with NDVI variation. Pearson et al., (2020) found a negative association between residential NDVI variation and rectum microbiome diversity. Taylor et al., (2018) found significant positive associations between general, personal and psychological well-being and NDVI (mean and standard deviation) in two Australian cities, but not in both cities in New Zealand. Higher levels of residential NDVI (mean and variation) were associated with lower odds of coronary heart disease and stroke (Pereira *et al.* 2012), and adult obesity (Pereira *et al.* 2013). Similarly, these studies found mixed results when analysing the correlation between NDVI (mean and variation) and other biodiversity measures, such as species richness. More evidence is needed to understand if NDVI metrics are accurate proxies for biodiversity in urban environments.

In addition to the considerations of biodiversity characteristics and measurement, metrics of proximity, exposure and accessibility to green- and bluespaces greatly vary between studies, and there is of yet no widely-recognised standard approach or recommendation to measure this (Ekkel & de Vries 2017; Labib *et al.* 2020b). Commonly used units include administrative boundaries (e.g. White et al., 2013) and Euclidean buffer zones (e.g. Gascon et al., 2018).

These both suffer from issues relating to size, unaccounted for access problems and arbitrary distances and boundaries. Network buffer zones attempt to address the latter issues (e.g. Pereira et al., 2012; Astell-Burt and Feng, 2019). However, they are still prone to problems pertaining to optimum distance selection. Euclidean and network distance to the nearest green- and/or bluespace is also a common exposure metric (e.g. Krekel et al., 2016; Kruize et al., 2020), but this does not account for access to multiple sites.

Distance decay functions are an alternative method of capturing residential exposure to green- and bluespaces. This method allows for every open space to be included in the model, but weights the effect by distance. Therefore, the effect of nearby open spaces is weighted more than those that are further away. While being a common method applied in other fields, such as human geography and ecology, it has rarely been used in the nature-well-being literature (Labib *et al.* 2020b). Egorov et al., (2017) use exponential distance-decay weighting to assess the impact of residential vegetation on allostatic load. They find a significant positive relationship between vegetation and markers of chronic illness, and that the importance of vegetation decreases with distance from the residential address. Saw et al., (2015) use a distance-decay function to assess well-being and proximity to greenspaces in Singapore and find no significant relationships. Other studies attempt to capture distance-decay effects by using nested buffers sizes (e.g. Requia et al., 2016), but this still requires distances to be defined. Using a distance-decay function has the benefit of not requiring any predetermined distance thresholds.

5.2.1 Key approaches and questions

In this study, we address the following questions:

1. Are particular habitats, habitat diversity, and biodiversity associated with subjective well-being?
2. Are there any associations between metrics of habitat, habitat diversity and biodiversity?
3. Do different methods for capturing exposure yield different results?

To address these questions we explored the relationship between habitats and biodiversity and subjective well-being in Greater London. In July 2019, London became the world's first National Park City. This makes it a particularly interesting urban area to study as it has a current agenda to improve the quality and use of its natural environments. London's parks and open spaces are estimated to save the city £950 million in health care costs (Mayor of London 2020), but London's biodiversity is following the same declining trajectory as that in England and the UK overall. In England, more species are experiencing population decreases than increases, and 13% of species in England are threatened with extinction (State of Nature Partnership 2019). Uncovering the potential importance of biodiversity on supporting human health and well-being is likely to improve the support for, and protection of, biodiversity in London.

We used a range of detailed and highly resolved databases to calculate habitat and biodiversity metrics across Greater London. We used a detailed habitat dataset and a species recordings database to capture habitat and species diversity across the city. Due to some habitat types having relatively small coverage in the city, we created a new set of habitat categories, based upon shared characteristics of habitat types. We created the following categories: grassland, maintained, use, water, wet, wild and woodland (see Table S5.2 for category composition). We calculated mean and standard deviation NDVI scores from remotely sensed imagery as they are commonly used measures of vegetation and biodiversity (Pearson *et al.* 2020).

We conducted the analysis using two different approaches to capturing exposure. The first method examines the relationship with biodiversity within an individual's residential neighbourhood. We used the lower super output area (LSOA) as the administrative boundary and calculated habitat and biodiversity metrics for each LSOA inhabited by an individual in our sample population. This is a commonly used boundary and has the benefits of many explanatory variables available to this level.

The second approach was to examine habitat and biodiversity within London's open spaces, and then to calculate exposure to these sites using distance-decay functions. We derived habitat and biodiversity metrics for all open spaces sites (OSSs) in Greater London, and then used distance-decay functions from an individual's 6-digit postcode centroid to calculate that person's "exposure" to habitat and biodiversity across the entire city. This method assumes that spaces further away will have less of an effect on an individual's well-being than those that are closer. It has the benefit of being able to capture the effect of all OSSs, not just the single closest for example, and it also avoids limiting the analysis via arbitrary boundaries or distances surrounding a resident's locations.

We use a large sample size of individuals from two large panel datasets, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS). Despite both surveys designed to be nationally representative, there are important differences in their spatial structure, demographic composition (due to differential rates of attrition), and time period of data collection. Using two different surveys allows us to examine these different population samples and time periods, and to explore the impact that these differences have on the relationships between well-being and the natural environment. We take advantage of the panel nature of the data by using fixed effects. Fixed effects have a significant advantage over cross-sectional correlations as it allows us to isolate within person variation as opposed to between person variation. We effectively follow the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits) that could be related to both biodiversity and subjective well-being. Many studies that examine the relationship between well-being and nature conduct cross-sectional analysis. This approach carries endogeneity issues which make the inference of causality difficult. Using longitudinal data and fixed effects regression allowed us to reduce endogeneity bias in our analysis.

We used three measures of subjective well-being: life satisfaction, mental distress (measured by the General Health Questionnaire (GHQ)) and self-reported general health. Subjective measures of well-being have been shown to have a high scientific standard in terms of internal consistency, reliability, and validity. All three measures are captured in both the BHPS and UKHLS. Life satisfaction, mental health and general health are commonly used measures in well-being surveys, and within the well-being and nature literature (e.g. White et al., 2013; Mears et al., 2019; Pasanen et al., 2019). The GHQ is a commonly used screening tool which helps to diagnose mood disorders. It is widely used in literature as a measure of mental health (Gascon *et al.* 2015). We also make use of a suite of socio-demographic and spatial explanatory variables, those that are in the panel survey datasets and also additional datasets that are publicly available, to address our research questions.

5.3 Methods

5.3.1 Open space sites (OSS)

We use the Open Space Sites (OSSs) database produced and maintained by Greenspace Information for Greater London CIC (GiGL). This spatial dataset is built and updated by each London borough. GiGL define OSSs as 'undeveloped land which has an amenity value, or has potential for amenity value' (Greenspace Information for Greater London CIC 2019b). It includes both public and private spaces, such as parks, commons, golf courses, playing fields, allotments and civic spaces, but excludes private gardens. There are 12,631 OSS sites in the database across Greater London (Figure 5.1).

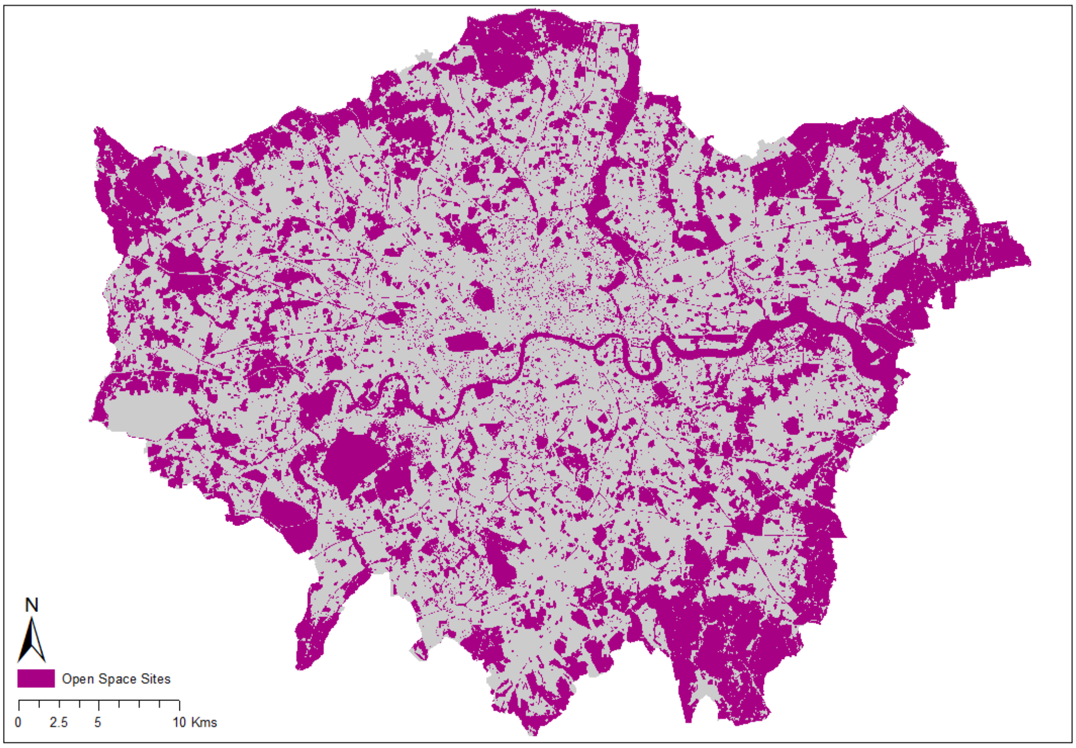

Figure 5.1. Open Space Sites (OSSs) of Greater London, as maintained by Greenspace Information for Greater London CIC (GiGL) [obtained 12th December 2018].

5.3.2 Habitat data

We use the GiGL habitat data layer for the entire Greater London region (see Figure S5.1 in appendix). A survey methodology was developed specifically for London by the Greater London Council and the London Wildlife Trust, and is similar to an Extended Phase 1 survey. The data was collected on a rolling programme from the mid-eighties to 2009. The current GiGL habitat dataset includes this baseline survey, as well as any other standard survey conducted since, using Extended Phase 1 or the National Vegetation Classification (NVC). Given that the majority of data records use the Extended Phase 1 instrument, all NVC entries have been converted to Extended Phase 1 categories using the JNCC habitat correspondence table (JNCC 2008).

The habitat data contains 40 habitat categories, including acid grassland, chalk grassland, allotments, native woodland, non-native woodland, river and still water (see Table S5.1 in appendix). Each polygon contains an estimated percentage cover for each habitat category present, for any open space larger than 0.25 ha. The area of each habitat polygon that intersected with an LSOA or OSS was calculated. Because the exact location of each habitat is not known, we calculated the percentage habitat cover of each habitat category of each intersection. The data were carefully cleaned to avoid duplicate and overlapping polygon areas, leaving 19,501 polygons from an initial set of 20,124. Due to problems with small sample sizes of certain habitat types, we created new habitat categories based on the dominant habitat characteristics: grassland, maintained, use, water, wet, wild and woodland (see Table S5.2 for category composition).

We found 53% (10,383 sites) of OSS sites contained habitat data. Of those sites that contained habitat data, 90% (9341 sites) of the OSS sites contained >95% habitat data and <1% of OSS sites (202 sites) had <1% habitat data. We calculated the percentage cover of each habitat type and habitat category for each LSOA and OSS. We then calculated diversity scores based on habitat types for each LSOA and OSS. The types Not available (HINA) Not surveyed (NTSV), and Other (OTHR) were merged into one single habitat type, and Bare artificial (BATH) was removed. We then calculated three different habitat diversity metrics for each LSOA and OSS: richness, Shannon Diversity Index (H) and Simpson’s Index of Diversity (1-D) (see Figures S5.2, S5.3 and S5.4 in appendix). Richness captures the number of habitat types within an area. The Shannon Index and Simpson’s Index of Diversity both account for the number of habitat types, and their relative proportion within an area. They differ in how they treat abundance: the Shannon Index reflects evenness and the Simpson’s Index of Diversity reflects dominance. Shannon Index values are generally found between 1.5-3.5, with diversity values increasing as richness and evenness increase.

$$H = -\sum_{i=1}^{m} (P_i) \ln(P_i)$$

H is Shannon Diversity Index, P_i refers to the proportion of a habitat type (*i)* in a given area (LSOA or OSS), m is the number of habitat types in a given area.

Simpson's Index values range between 0 to 1. We use the inverse Simpson's Index, called Simpson's Index of Diversity so that values closer to 0 indicate lower diversity and those closer to 1 indicate higher diversity.

$$1 - D = \sum_{i=1}^{m} (P_i)^2$$

D is Simpson's Diversity Index, P_i refers to the proportion of a habitat type (*i)* in a given area (LSOA or OSS), m is the number of habitat types in a given area.

5.3.3 Biodiversity data

We use the GiGL species database to calculate biodiversity metrics. The database holds over 4.1 million species records for Greater London, collected by expert volunteer recorders, professional surveyors, and members of the public. Each record is georeferenced, and checked for quality and accuracy by the GiGL Advisory Panel and species experts. We extracted records for all butterflies, birds and plants (excluding fungi and lichen), and calculated species richness for each LSOA and OSS (see Figures S5.5, S5.6 and S5.7 in appendix). Given issues of uneven sampling both spatially and temporally, we do not include abundance data and only calculate species richness. Each record relates to an individual species sighting in a particular location on a specific date. Each record is a point, and only includes those records with a spatial accuracy to within 10m or 100m. All records with missing species information or recording coordinates and those with a survey date of 1990 or earlier were deleted prior to analysis. Similarly any records with only a taxonomy level higher than species level were removed.

Butterflies

Following cleaning, the butterfly subset contained 254,253 records for Greater London. In the OSS analysis, 25.5% of OSS sites (3219 sites) had at least 1 butterfly record within it. 8% of sites (970 sites) had only 1 butterfly species recorded, and 2.5% (315 sites) had 20 or more species recorded.

Birds

The bird subset contained 1,141,228 records for Greater London. In the OSS analysis, 43% of OSS sites (5487 sites) had at least 1 bird record within it. Overall, 9% of sites (1142 sites) had only 1 bird species recorded in it, and over 5% (713 sites) had 20 or more bird species recorded.

Plants

The plant subset contained 963,745 records for Greater London. In the OSS analysis, 65.4% of OSS sites (8261 sites) had at least 1 plant species record within it. Overall, 2% of OSS sites (267 sites) had only 1 plant species recorded in it, and 42% of sites (5294 sites) had 20 or more plant species recorded. In fact, over 1% of sites (164 sites) had 200 or more plant species recorded.

5.3.4 NDVI data

We used two different NDVI layers in our analysis. To reflect the time periods of our two sample populations we obtained the best remote sensing imagery available for years 2000 and 2018. To represent the year 2000, we used Landsat 7 images (30x30m resolution). The images were acquired for May-September 2000, representing the time of the year with highest greenness values. This time period allowed us to acquire sufficient numbers of low-cloud images to calculate NDVI scores. To represent 2018, we obtained Sentinel 2 imagery (10x10m resolution). The images were acquired for the month of June that year, this time period was again sufficient to acquire low-cloud imagery at the time of year of high vegetation greenness.

We acquired Surface Reflectance Tier 1 imagery for both years, only using images with <25% cloud cover. Images were corrected for clouds and cloud shadows, and median NDVI scores were calculated for each time period to give a final NDVI score for every grid cell across Greater London. We used Google Earth Engine to obtain and process images and calculate NDVI values.

NDVI is calculated as follows:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

NIR and RED refer to the spectral reflectance values acquired in the near-infrared and the visible red wavelengths respectively. NDVI ranges from -1 to 1 with higher number representing more green and health vegetation. '-1' represents very high reflectance in the red band with little near-infrared reflectance, suggesting ice or cloud. Water and built surfaces have NDVI values near 0.

We calculated the mean and standard deviation NDVI values for each sample unit (LSOA and OSS). To avoid negative NDVI values leading to misleading statistics, all pixels with a value between -1 and 0 were removed first. This meant water bodies were not included in this part of the analysis.

5.3.5 Sample population

We used population samples from both the BHPS and the UKHLS, both are available as part of the Understanding Society project (University of Essex. Institute for Social and Economic Research 2019b, 2019a). Both surveys are large multi-year panel datasets collecting individual and household information from a representative sample population. Demographic, socio-economic, health and geographic data are collected in the dataset, as well as that pertaining to attitudes, opinions, and values. The BHPS ran from 1991 to 2018 (waves 1-18) and collected information from over 10,000 individuals (5000 households). Data collection for each wave in the BHPS was undertaken within a sample year. We use waves 1-8 from the UKHLS (2009 – 2018) and contains information pertaining to over 50,000 individuals (40,000 households). Data collection for each wave in the UKHLS was undertaken over a two-year overlapping window.

Each individual in the BHPS and UKHLS has a geographic identifier as an easting and northing (centroid of the postcode unit). A postcode unit can represent part of a street or an individual building (dependent on mail volume). This highly specific location data was accessed using the UK Data Service Secure Lab environment. We included all adults (categorised as 16+ years) with eastings and northings pertaining to Greater London in this study, and assigned each individual the corresponding LSOA code based on their postcode identifier.

5.3.6 Well-being

We use three measures of subjective well-being: life satisfaction question, the General Health Questionnaire (GHQ) and self-reported general health. All three measures are captured in both the BHPS and the UKHLS, and are consistent across both surveys (Figure 5.2). Life satisfaction is based on the respondents' answer to the following questions: 'How dissatisfied or satisfied are you with life overall?' Respondents give a single reply from a Likert scale with options ranging from 7 ('completely satisfied') to 1 ('completely unsatisfied').

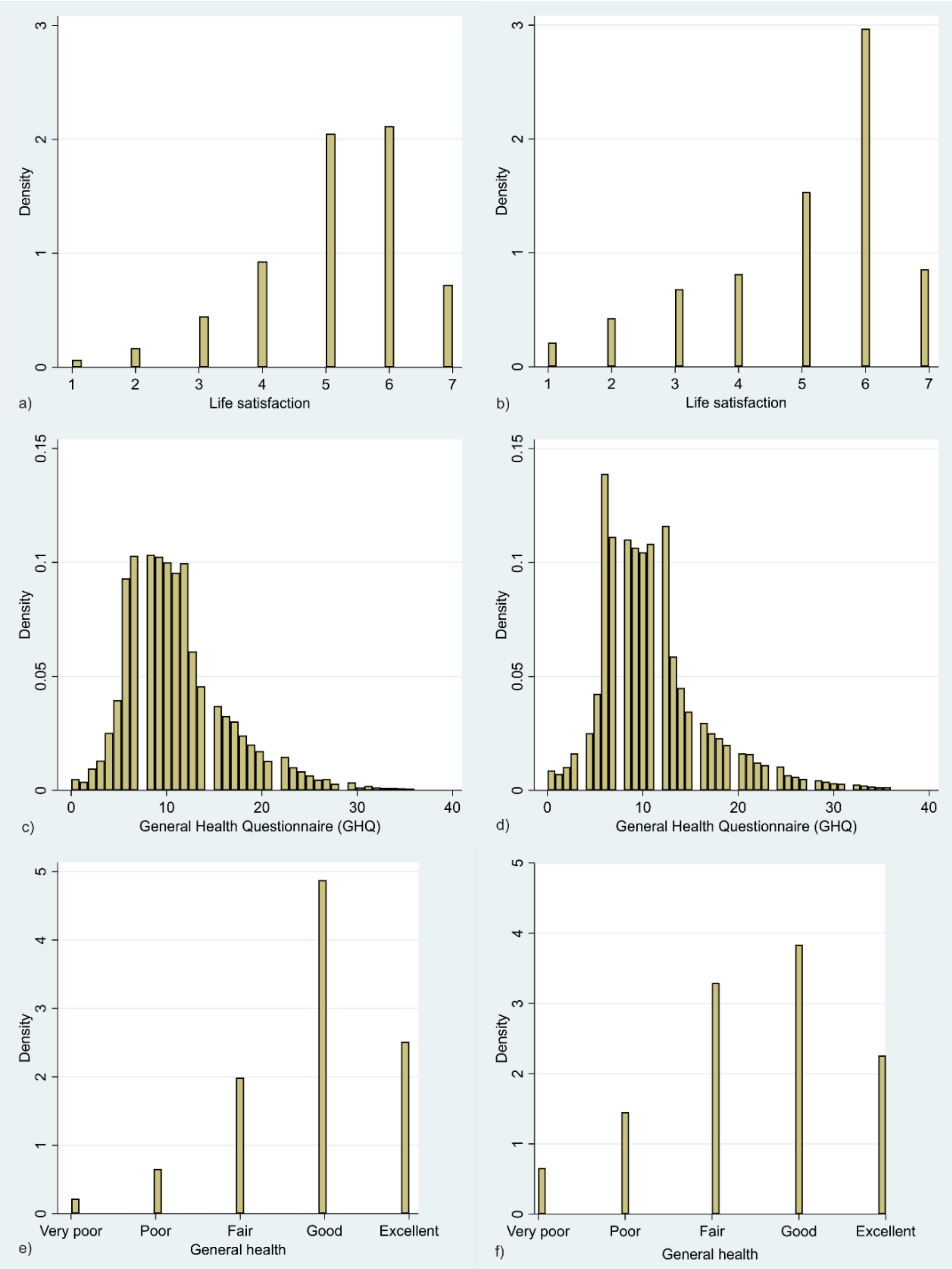

Figure 5.2. The distribution of subjective well-being across the population samples (BHPS: a, c and e; UKHLS: b, d, and f). The y-axis represents the density of observations per bin: the height of the bars are scaled so that the sum of their areas equals 1.

In this study we used the 12-item short form of the GHQ. Respondents are asked to self-assess against six positive and six negative statements (e.g. I am capable of making decisions and I think of myself as worthless). Respondents give a single reply to each statement on a four-point scale, based on their own evaluation of how the “past few weeks” compare with “usual”. The scale ranges from 0 (not at all), 1 (no more than usual), 2 (rather more than usual), and 3 (much more than usual). This gives an overall score ranging from 0 (very low mental distress) to 36 (very high mental distress).

Self-reported general health is asked in both the BHPS and the UKHLS but the question slightly differs between the two surveys. In the BHPS, respondents are asked “Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been...?” In the UKHLS, respondents are asked “In general, would you say your health is...?” In both surveys the respondent gives a single answer on a Likert scale ranging from 1 (excellent) to 5 (very poor). In this analysis, we inverted to scale, so that 5 represented excellent health and 1 very poor health, for ease of interpretation. In the UKHLS waves 1-5, the question is asked in the main survey, and in waves 6-8 it is asked in the self-complete section.

The GHQ was asked in all 18 waves of the BHPS and all 8 waves of the UKHLS, the life satisfaction question was only asked in 12 waves of the BHPS and all 8 waves of the UKHLS, and Self-reported general health was asked in 17 of the 18 waves in the BHPS and in all 8 waves of the UKHLS. Therefore the number of observations in the life satisfaction and general health models are lower than the GHQ models.

5.3.7 Control data

We included commonly observed predictors of an individual’s subjective well-being in our regression analysis. These include individual-, household-, and neighbourhood- level factors. Specifically at the individual level we use age, higher education, relationship status, health, labour force status, commuting time. At the household level we use income, living with children, residence type (only available in the BHPS) and household space. A wave variable was included to account for any natural temporal progression in the data or anything that may have occurred that is specific to that wave, such as the survey instrument used, or national or global events. Table 5.1 provides a description of each variable used and Table 5.2,Table 5.3Table 5.4 provide descriptive statistics for the overall datasets for Greater London and the estimation samples used for each model. We can see that each model uses an estimation sample that is very similar to the overall dataset. Missing data across all variables can be found in the BHPS and the UKHLS and is due to wave nonresponse, item nonresponse, and respondent attrition. Where possible and appropriate we have imputed missing values from adjacent waves.

It is likely that the relationship between well-being and public natural environments is affected by socio-economic factors pertaining to neighbourhoods. Therefore we included the English Indices of Multiple Deprivation. These are calculated every 2-5 years by the Department for Communities and Local Government (DCLG), and are based on 37 separate indicators, organised across seven distinct domains of deprivation (Department for Communities and Local Government 2010). In this analysis we included the Income Deprivation domain and the Employment Deprivation domain, which measure the proportion of the population experiencing deprivation relating to low income and benefit claiming respectively. We also included the Crime Deprivation domain which reflects the risk of personal and material victimisation, and the Education Deprivation domain which relates to school performance and higher education rates.

The indices of deprivation are only available down to the lower super output area (LSOA) level (4,765 LSOAs in London). LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). The mean area of a London LSOA is 3.3km^2. Due to population fluctuations approximately 5% of LSOAs in the UK changed in 2011 (split, merged or deleted), so here, for consistency, we used the 2002 LSOA structure throughout the study.

It is also possible that air pollution levels affect the relationship between the natural environment and well-being (Laffan 2018; Yuan *et al.* 2018). Here we included annual ambient outdoor NO_2 levels from the UK's Department for Environment, Food and Rural Affairs (Defra) as pollution-climate modelled values (Defra 2016). These are outputs based on dispersion modelling using point sources of known emission levels (e.g. monitoring stations, power stations, roadsides) and UK meteorological data, and are available as 1km x 1km grids for the UK as the annual mean NO_2 in μg/m^3. Each LSOA was given the pollution value of the nearest NO_2 point to each LSOA population-weighted centroid. The pollution values were then attributed to every individual residing in the corresponding LSOA, BHPS observations were assigned NO_2 for the year 2008, and UKHLS individuals assigned that for 2014.

Table 5.1. Variable descriptions.

	Variable description
Life satisfaction	Respondent's self-reported life satisfaction (scale 1 to 7)
GHQ	Respondent's self-reported General Health Questionnaire score (scale 0 to 36)
General health	Respondent's self-reported general health (scale 1 to 5)
Habitat categories	Percentage of habitat cover in LSOA or OSS (see Appendix for details on each habitat type)
ACDG	Acid grassland
ALTA	Allotments
AMNG	Amenity grassland
ARBL	Arable
BASG	Chalk grassland
BATH	Bare artificial
BOGG	Bog
BSAR	Bare ground
BRAK	Bracken
CONW	Conifer woodland
DTWF	Ditch
FNCR	Carr
HINA	Not available
HTHL	Heathland
IMSS	Imp grassland
IRAG	Imp-agri grassland
NHRG	Herb rich grassland
NNBW	Non-native woodland
NNHD	Non-native hedge
NSIG	Semi-imp grassland
NTSV	Not surveyed
NVBW	Native woodland
NVHD	Native hedge
NWAS	Woodland & scrub
ORCH	Orchard
OTHR	Other

PLSH	Shrubbery
RDEP	Ruderal
RDSW	Reed
RGHL	Roughland
RWRS	River
SCRB	Scrub
SCTR	Scat trees
STMS	Saltmarsh
STWC	Still water
TLHB	Tall herb
TYSW	Swamp
VEGW	Vegetated walls
WOOD	Woodland
WTMV	Wet marginal
Habitat categories	Percentage of habitat cover in LSOA or OSS
Grassland	Acid grassland (ACDG) + Amenity grassland (AMNG) + Chalk grassland (BASG) + Imp-agri grassland (IRAG) + Herb rich grassland (NHRG) + Semi-imp grassland (NSIG)
Maintained	Amenity grassland (AMNG) + Non-native hedge (NNHD) + Native hedge (NVHD) + Shrubbery (PLSH) + Tall herb (TLHB)
Use	Allotments (ALTA) + Amenity grassland (AMNG) + Arable (ARBL) + Orchard (ORCH) + Vegetated walls (VEGW)
Water	River (RWRS) + Still water (STWC)
Wet	Bog (BOGG) + Ditch (DTWF) + Improved grassland (IMSS) + Reed (RDSW) + Saltmarsh (STMS) + Swamp (TYSW) Wet marginal (WTMV)
Wild	Bog (BOGG) + Bracken (BRAK) + Fen carr (FNCR) + Healthland (HTHL) + Ruderal (RDEP) + Roughland (RGHL) + Scrub (SCRB) + Swamp (TYSW) + Wet marginal (WTMV)
Woodland	Conifer woodland (CONW) + Non-native broadleaf woodland (NNBW) + Native broadleaf woodland (NVBW) + Scat trees (SCTR) + Woodland & scrub (NWAS) + Woodland (WOOD)
Habitat diversity	
Richness	Number of habitats per LSOA or OSS
Shannon Index	Diversity Index score per LSOA or OSS (scale 0 to 4)
Simpson's Index	Diversity Index score per LSOA or OSS (1-Simpson's Index; scale 0 to 1)
Biodiversity	

Butterfly richness	Number of butterfly species recorded per LSOA or OSS
Bird richness	Number of bird species recorded per LSOA or OSS
Plant richness	Number of plant species recorded per LSOA or OSS
Total richness	Total number of all butterfly, bird and plant species recorded per LSOA or OSS
Biodiversity	
NDVI mean	Mean NDVI score per LSOA or OSS for 2000 (BHPS) or 2018 (UKHLS)
NDVI standard deviation	Standard deviation of NDVI score per LSOA or OSS for 2000 (BHPS) or 2018 (UKHLS)
Spatial control variables	
Income deprivation	Indices of Multiple Deprivation – deprivation relating to low income and social benefit in the LSOA
Employment deprivation	Indices of Multiple Deprivation – deprivation relating to benefit claimants in the LSOA
Education deprivation	Indices of Multiple Deprivation – deprivation relating to school performance and higher education rates in the LSOA
Crime deprivation	Indices of Multiple Deprivation – deprivation relating to the risk of personal and material victimisation in the LSOA
NO_2	Mean annual ambient nitrogen dioxide (NO_2) in respondent's residential LSOA in 2008 ($\mu g/m^3$)
Age (yrs)	
16-25	Respondent's age is between 16-25 years (yes/no)
26-35	Respondent's age is between 26-35 years (yes/no)
36-45	Respondent's age is between 36-45 years (yes/no)
46-55	Respondent's age is between 46-55 years (yes/no)
56-65	Respondent's age is between 56-65 years (yes/no)
66-75	Respondent's age is between 66-75 years (yes/no)
75+	Respondent's age is between 75+ years (yes/no)
University-level qualification	Respondent has a university –level qualification (yes/no)
In a relationship	Respondent is married or living as a couple (yes/no)
Living with children	Living with own children (<16 years old) (yes/no)
Annual household income	Log equivalent annual household income (income divided by square root of household size (number of people))
Health condition	Respondent self-reports a health condition that limits the type of work or amount of work they can do (yes/no)
Employment status	
Employed	Respondent is employed (yes/no)
Unemployed	Respondent is unemployed or disabled (yes/no)

Retired Caring for family In training Other	Respondent is retired (yes/no) Respondent is caring for family (yes/no) Respondent is in training (yes/no) Respondent is in another type of status (yes/no)
House type (BHPS only)	
Detached Semi-detached Terraced Flat Other	Respondent lives in a detached house (yes/no) Respondent lives in a semi-detached house (yes/no) Respondent lives in a terraced house (yes/no) Respondent lives in a flat (yes/no) Respondent lives in another type of dwelling e.g. bedsit (yes/no)
Household space	
<1 room per person 1 - < 3 rooms per person 3 ≥ rooms per person	Less than 1 room per person in the house (yes/no) Between 1 and under 3 rooms per person in the house (yes/no) Three or more rooms per person in the house (yes/no)
Commuting time	
None ≤ 15 mins 16-30 mins 31-50 mins ≥ 50 mins	Respondent has no commute (yes/no) Respondent has a commute of 15 minutes or less (yes/no) Respondent has a commute of 16-30 minutes or less (yes/no) Respondent has a commute of 31-50 minutes or less (yes/no) Respondent has a commute of over 50 minutes (yes/no)
Other	
Wave	BHPS wave 1-18 or UKHLS wave 1-8 (numbered 19-26)

Table 5.2. Descriptive statistics of all habitat and biodiversity variables for the full survey samples, for the LSOA and distance-decay analyses.

	All BHPS		All UKHLS	
	Mean (St. Dev.) (N=15,682)		Mean (St. Dev.) (N=50,013)	
	LSOA	Distance-decay	LSOA	Distance-decay
All OSS area	21.33 (21.64)	-	19.87 (20.05)	-
Distance	-	0.00 (0.01)	-	0.02 (0.44)
Area	-	0.01 (0.04)	-	0.06 (1.74)
Habitat types				
ACDG (Acid grassland)	0.24 (2.15)	5.83 (85.22)	0.24 (1.89)	4.90 (173.30)
ALTA (Allotments)	0.73 (2.91)	1.70 (31.37)	0.43 (1.80)	2.29 (68.62)
AMNG (Amenity grassland)	6.63 (8.68)	14.75 (94.35)	5.96 (8.42)	59.40 (1509.05)
ARBL (Arable)	0.47 (2.79)	2.56 (25.47)	0.20 (2.44)	5.85 (198.39)
BASG (Chalk grassland)	0.04 (0.27)	1.49 (44.01)	0.03 (0.40)	0.73 (15.50)
BATH (Bare artificial)	2.99 (6.35)	4.34 (40.45)	2.75 (5.11)	21.90 (448.12)
BOGG (Bog)	0.00 (0.05)	0.00 (0.02)	0.00 (0.02)	0.02 (1.43)
BRAK (Bracken)	0.01 (0.15)	0.19 (1.27)	0.01 (0.32)	0.22 (4.35)
BSAR (Bare ground)	0.19 (1.07)	1.46 (18.12)	0.21 (1.04)	12.93 (758.90)
CONW (Conifer woodland)	0.02 (0.19)	0.10 (1.01)	0.01 (0.23)	0.19 (4.96)
DTWF (Ditch)	0.01 (0.06)	0.39 (5.92)	0.01 (0.06)	0.47 (19.47)
FNCR (Carr)	0.00 (0.06)	0.12 (3.27)	0.00 (0.06)	0.03 (0.60)
HINA (Not available)	0.07 (0.71)	0.08 (0.24)	0.33 (4.30)	0.20 (3.33)
HTHL (Heathland)	0.00 (0.09)	0.10 (2.00)	0.01 (0.32)	0.08 (2.30)
IMSS (Imp grassland)	0.03 (0.63)	0.09 (0.73)	0.10 (0.79)	0.35 (9.57)
IRAG (Imp-agri grassland)	0.62 (3.25)	3.44 (41.21)	0.29 (2.26)	10.50 (312.05)
NHRG (Herb rich grassland)	0.28 (1.36)	1.37 (40.30)	0.19 (1.21)	2.86 (72.80)
NNBW (Non-native woodland)	0.48 (1.30)	1.85 (47.22)	0.40 (1.40)	26.75 (1048.61)
NNHD (Non-native hedge)	0.04 (0.14)	0.08 (0.59)	0.06 (0.24)	0.12 (1.56)
NSIG (Semi-imp grassland)	2.44 (6.20)	8.00 (77.08)	1.85 (4.70)	28.04 (371.35)
NTSV (Not surveyed)	0.60 (3.74)	0.66 (7.09)	0.20 (1.97)	2.32 (101.10)
NVBW (Native woodland)	1.08 (3.26)	10.14 (178.20)	1.04 (3.89)	31.39 (836.67)

	All BHPS		All UKHLS	
	Mean (St. Dev.) (N=15,682)		Mean (St. Dev.) (N=50,013)	
	LSOA	Distance-decay	LSOA	Distance-decay
NVHD (Native hedge)	0.16 (0.43)	0.52 (6.51)	0.12 (0.44)	1.74 (32.44)
NWAS (Woodland & scrub)	0.00 (0.06)	0.00 (0.21)	0.00 (0.05)	0.04 (1.65)
ORCH (Orchard)	0.01 (0.12)	0.11 (4.19)	0.01 (0.12)	0.04 (0.91)
OTHR (Other)	0.06 (0.41)	0.45 (26.68)	0.06 (0.71)	6.02 (409.84)
PLSH (Shrubbery)	0.27 (0.54)	0.59 (5.27)	0.33 (0.79)	2.46 (85.63)
RDEP (Ruderal)	0.27 (1.27)	1.27 (12.72)	0.28 (1.13)	18.50 (1193.32)
RDSW (Reed)	0.06 (0.37)	0.09 (0.80)	0.03 (0.32)	0.37 (9.55)
RGHL (Roughland)	0.59 (2.08)	1.69 (24.47)	0.36 (1.48)	6.25 (171.29)
RWRS (River)	0.26 (1.91)	0.82 (18,79)	0.62 (3.66)	1.92 (71.37)
SCRB (Scrub)	0.85 (1.48)	5.95 (86.60)	0.73 (1.43)	38.33 (1392.98)
SCTR (Scat trees)	1.54 (2.11)	4.84 (40.34)	1.48 (2.18)	11.03 (148.85)
STMS (Saltmarsh)	0.00 (0.02)	0.01 (0.11)	0.00 (0.05)	0.02 (0.46)
STWC (Still water)	0.26 (1.30)	2.25 (38.40)	0.68 (3.37)	22.63 (1020.83)
TLHB (Tall herb)	0.58 (1.15)	1.80 (15.64)	0.47 (1.11)	24.40 (757.83)
TYSW (Swamp)	0.03 (0.21)	0.09 (3.00)	0.02 (0.29)	0.21 (5.80)
VEGW (Vegetated walls)	0.03 (0.70)	0.04 (0.32)	0.03 (0.48)	0.29 (16.63)
WOOD (Woodland)	0.00 (0.00)	0.02 (0.19)	0.01 (0.41)	0.09 (3.18)
WTMV (Wet marginal)	0.04 (0.22)	0.23 (13.64)	0.04 (0.20)	1.39 (39.42)
Habitat categories				
Grassland	10.24 (13.02)	34.88 (211.25)	8.57 (11.23)	106.43 (1669.13)
Maintained	7.69 (9.23)	17.73 (105.22)	6.95 (9.05)	88.12 (1704.58)
Use	7.88 (7.78)	19.16 (103.27)	6.63 (8.97)	67.87 (1527.07)
Water	0.53 (2.41)	3.07 (56.01)	1.30 (5.18)	24.55 (1028.97)
Wet	0.17 (0.95)	0.89 (18.25)	0.20 (1.12)	2.83 (63.51)
Wild	1.79 (3.39)	9.64 (104.07)	1.46 (2.75)	63.04 (1963.11)
Woodland	3.13 (4.34)	16.95 (233.11)	2.94 (5.04)	69.50 (1611.99)
Habitat diversity				
Species richness	9.10 (5.39)	0.00 (0.02)	8.13 (5.15)	0.02 (0.56)

	All BHPS		All UKHLS	
	Mean (St. Dev.) (N=15,682)		Mean (St. Dev.) (N=50,013)	
	LSOA	Distance-decay	LSOA	Distance-decay
Shannon’s Index	0.63 (0.55)	0.00 (0.00)	0.56 (0.51)	0.004 (0.14)
Simpson’s Index	0.28 (0.24)	0.00 (0.00)	0.25 (0.23)	0.002 (0.07)
Biodiversity				
Butterfly richness	5.38 (8.79)	0.00 (0.01)	5.12 (8.04)	0.01 (0.12)
Bird richness	18.73 (28.25)	0.00 (0.01)	15.25 (26.65)	0.01 (0.19)
Plant richness	71.26 (102.19)	0.01 (0.06)	62.18 (78.35)	0.05 (0.81)
Total richness	95.38 (128.77)	0.02 (0.08)	82.55 (102.84)	0.06 (0.89)
NDVI				
NDVI mean	0.43 (0.10)	0.00 (0.01)	0.33 (0.10)	0.007 (0.22)
NDVI standard deviation	0.12 (0.03)	0.0 (0.00)	0.16 (0.03)	0.00 (0.09)

Table 5.3. Descriptive statistics of the dependent and control variables for the full survey samples

	All BHPS			All UKHLS		
	N (total) N=15,682	Cell count	Mean (St. Dev.) or %	N (total) N=50,013	Cell count	Mean (St. Dev.) or %
Life satisfaction	9,138	9,138	5.15 (1.25)	35,410	35,410	5.05 (1.51)
GHQ	14,301	14,301	11.18 (5.41)	36,898	36,898	10.98 (5.66)
General health	14,710	14,710	3.86 (0.93)	48,156	48,156	3.49 (1.11)
Spatial control variables						
Income deprivation	15,682	15,682	0.17 (0.10)	50,013	50,013	0.23 (0.13)
Employment deprivation	15,682	15,682	0.09 (0.04)	50,013	50,013	0.11 (0.05)
Education deprivation	15,682	15,682	13.77 (10.74)	50,013	50,013	16.11 (10.52)
Crime deprivation	15,682	15,682	0.35 (0.59)	50,013	50,013	0.50 (0.56)
NO_2	15,682	15,682	28.73 (5.90)	50,013	50,013	29.45 (7.07)
Age (yrs)						
16-25	15,682	2,778	17.71%	49,988	9,302	18.61%
26-35	15,682	3,381	21.56%	49,988	9,615	19.23%
36-45	15,682	2,860	18.24%	49,988	10,592	21.19%
46-55	15,682	2,542	16.21%	49,988	8,908	17.82%
56-65	15,682	1,882	12.00%	49,988	5,596	11.19%
66-75	15,682	1,244	7.93%	49,988	3,775	7.56%
75+	15,682	995	6.34%	49,988	2,200	4.40%
University-level qualification	15,098	4,190	27.75%	48,342	21,531	44.54%
In a relationship	15,676	9,097	58.03%	49,878	27,707	55.55%
Living with children	15,682	3,764	24.00%	50,013	16,024	32.04%
Annual household income	15,176	15,176	7.18 (0.84)	49,635	49,635	7.39 (0.71)
Health condition	15,610	2,532	16.22%	49,854	12,916	25.91%
Employment status						
Employed	15, 613	9,576	61.34%	49,947	27,429	54.92%
Unemployed	15, 613	1,103	7.06%	49,947	5,540	11.09%
Retired	15, 613	2,524	16.17%	49,947	6,726	13.47%
Caring for family	15, 613	1,237	7.92%	49,947	4,547	9.10%

	All BHPS			All UKHLS		
	N (total) N=15,682	Cell count	Mean (St. Dev.) or %	N (total) N=50,013	Cell count	Mean (St. Dev.) or %
In training	15, 613	1,085	6.95%	49,947	5,361	10.73%
Other	15, 613	88	0.56%	49,947	344	0.69%
House type						
Detached	15,030	1,024	6.81%	-	-	-
Semi-detached	15,030	3,818	25.40%	-	-	-
Terraced	15,030	5,242	34.88%	-	-	-
Flat	15,030	4,642	30.88%	-	-	-
Other	15,030	303	2.02%	-	-	-
Household space						
<1 room per person	15, 275	1,153	7.55%	49,736	9,548	19.20%
1 - < 3 rooms per person	15, 275	11,846	77.55%	49,736	34,311	68.98%
3 ≥ rooms per person	15, 275	2,276	14.90%	49,736	5,877	11.82%
Commuting time						
None	14,427	6,026	41.77%	44,808	22,207	49.56%
≤ 15 mins	14,427	2,316	16.05%	44,808	4,749	10.60%
16-30 mins	14,427	2,417	16.75%	44,808	6,422	14.33%
31-50 mins	14,427	1,791	12.41%	44,808	5,547	12.38%
≥ 50 mins	14,427	1,877	13.01%	44,808	5,883	13.13%
Other						
Wave	15,682	15,682	-	50,013	50,013	-

Table 5.4. Descriptive statistics of the six model specifications.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
Life satisfaction	5.13 (1.23)	-	-	5.05 (1.51)	-	-
GHQ	-	11.23 (5.42)	-	-	11.00 (5.67)	-
General health	-	-	3.85 (0.93)	-	-	3.48 (1.10)
LSOA-level variables						
All OSS area	22.43 (22.12)	21.80 (21.72)	21.83 (21.71)	20.28 (20.42)	20.25 (20.39)	19.97 (20.25)
Habitat types						
ACDG (Acid grassland)	0.30 (2.53)	0.25 (2.23)	0.24 (2.19)	0.27 (2.08)	0.27 (2.06)	0.26 (2.00)
ALTA (Allotments)	0.75 (3.01)	0.74 (2.98)	0.74 (2.96)	0.43 (1.79)	0.43 (1.78)	0.42 (1.78)
AMNG (Amenity grassland)	6.62 (8.62)	6.61 (8.48)	6.64 (8.50)	5.98 (8.41)	6.01 (8.42)	5.96 (8.44)
ARBL (Arable)	0.47 (2.79)	0.47 (2.73)	0.47 (2.73)	0.21 (2.49)	0.21 (2.46)	0.20 (2.43)
BASG (Chalk grassland)	0.04 (0.28)	0.04 (0.28)	0.03 (0.27)	0.03 (0.44)	0.03 (0.43)	0.03 (0.43)
BATH (Bare artificial)	2.92 (6.11)	2.98 (6.25)	3.05 (6.45)	2.66 (4.92)	2.67 (4.93)	2.70 (5.02)
BOGG (Bog)	0.00 (0.07)	0.00 (0.06)	0.00 (0.06)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)
BRAK (Bracken)	0.01 (0.18)	0.01 (0.15)	0.01 (0.15)	0.02 (0.34)	0.02 (0.34)	0.02 (0.35)
BSAR (Bare ground)	0.21 (1.23)	0.19 (1.11)	0.20 (1.12)	0.21 (1.13)	0.21 (1.12)	0.21 (1.09)
CONW (Conifer woodland)	0.02 (0.19)	0.02 (0.19)	0.02 (0.19)	0.02 (0.25)	0.02 (0.24)	0.02 (0.24)
DTWF (Ditch)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)
FNCR (Carr)	0.00 (0.07)	0.00 (0.06)	0.00 (0.06)	0.00 (0.07)	0.00 (0.06)	0.00 (0.07)
HINA (Not available)	0.08 (0.79)	0.07 (0.70)	0.07 (0.70)	0.34 (4.37)	0.33 (4.31)	0.32 (4.16)
HTHL (Heathland)	0.00 (0.12)	0.00 (0.10)	0.00 (0.10)	0.02 (0.30)	0.01 (0.30)	0.01 (0.32)
IMSS (Imp grassland)	0.05 (0.77)	003 (0.62)	0.03 (0.63)	0.10 (0.80)	0.10 (0.79)	0.10 (0.80)
IRAG (Imp-agri grassland)	0.56 (2.81)	0.60 (3.14)	0.60 (3.13)	0.32 (2.35)	0.31 (2.31)	0.30 (2.25)
NHRG (Herb rich grassland)	0.28 (1.37)	0.29 (1.41)	0.29 (1.40)	0.18 (1.13)	0.19 (1.16)	0.18 (1.16)
NNBW (Non-native woodland)	0.47 (1.28)	0.49 (1.33)	0.48 (1.32)	0.42 (1.46)	0.42 (1.44)	0.41 (1.45)
NNHD (Non-native hedge)	0.05 (0.15)	0.04 (0.15)	0.04 (0.15)	0.06 (0.22)	0.06 (0.23)	0.06 (0.22)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
NSIG (Semi-imp grassland)	2.55 (6.42)	2.48 (6.27)	2.46 (6.23)	1.96 (4.92)	1.95 (4.88)	1.89 (4.77)
NTSV (Not surveyed)	0.68 (3.96)	0.66 (3.93)	0.66 (3.96)	0.24 (2.17)	0.23 (2.14)	0.22 (2.09)
NVBW (Native woodland)	1.18 (3.52)	1.10 (3.30)	1.10 (3.31)	1.14 (4.11)	1.13 (4.08)	1.09 (4.02)
NVHD (Native hedge)	0.16 (0.41)	0.16 (0.42)	0.16 (0.41)	0.13 (0.45)	0.13 (0.45)	0.13 (0.44)
NWAS (Woodland & scrub)	0.00 (0.08)	0.00 (0.06)	0.00 (0.05)	-	-	-
ORCH (Orchard)	0.01 (0.12)	0.01 (0.12)	0.02 (0.12)	0.01 (0.11)	0.01 (0.11)	0.01 (0.11)
OTHR (Other)	0.06 (0.47)	0.05 (0.41)	0.05 (0.41)	0.07 (0.74)	0.07 (0.73)	0.07 (0.74)
PLSH (Shrubbery)	0.28 (0.56)	0.27 (0.54)	0.27 (0.54)	0.32 (0.79)	0.32 (0.79)	0.33 (0.78)
RDEP (Ruderal)	0.29 (1.43)	0.28 (1.32)	0.28 (1.33)	0.27 (1.09)	0.27 (1.09)	0.27 (1.10)
RDSW (Reed)	0.06 (0.40)	0.06 (0.37)	0.06 (0.37)	0.03 (0.35)	0.03 (0.34)	0.03 (0.33)
RGHL (Roughland)	0.60 (2.04)	0.59 (2.03)	0.58 (2.01)	0.37 (1.53)	0.37 (1.53)	0.36 (1.48)
RWRS (River)	0.30 (2.09)	0.25 (1.80)	0.26 (1.87)	0.63 (3.69)	0.62 (3.64)	0.62 (3.65)
SCRB (Scrub)	0.86 (1.51)	0.86 (1.50)	0.86 (1.50)	0.75 (1.45)	0.75 (1.44)	0.74 (1.44)
SCTR (Scat trees)	1.59 (2.19)	1.55 (2.13)	1.55 (2.13)	1.46 (2.18)	1.47 (2.19)	1.47 (2.18)
STMS (Saltmarsh)	0.00 (0.03)	0.00 (0.02)	0.00 (0.02)	0.00 (0.05)	0.00 (0.05)	0.00 (0.05)
STWC (Still water)	0.34 (1.52)	0.26 (1.29)	0.26 (1.33)	0.69 (3.46)	0.70 (3.50)	0.67 (3.39)
TLHB (Tall herb)	0.58 (1.13)	0.58 (1.15)	0.58 (1.14)	0.67 (3.39)	0.48 (1.15)	0.47 (1.12)
TYSW (Swamp)	0.03 (0.21)	0.03 (0.21)	0.03 (0.20)	0.03 (0.33)	0.03 (0.32)	0.02 (0.31)
VEGW (Vegetated walls)	0.04 (0.88)	0.040 (0.75)	0.04 (0.76)	0.04 (0.54)	0.04 (0.51)	0.03 (0.50)
WOOD (Woodland)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.44)	0.01 (0.44)	0.01 (0.44)
WTMV (Wet marginal)	0.04 (0.22)	0.04 (0.23)	0.04 (0.23)	0.04 (0.21)	0.04 (0.21)	0.04 (0.21)
Habitat categories						
Grassland	10.36 (13.07)	10.27 (12.88)	10.26 (12.83)	8.75 (11.44)	8.76 (11.42)	8.62 (11.33)
Maintained	7.68 (9.16)	7.66 (9.03)	7.69 (9.04)	6.97 (9.02)	7.00 (9.04)	6.94 (9.06)
Use	7.90 (9.80)	7.87 (9.64)	7.89 (9.66)	6.67 (8.99)	6.69 (8.99)	6.63 (9.00)
Water	0.63 (2.70)	0.51 (2.32)	0.52 (2.40)	1.32 (5.26)	1.32 (5.25)	1.29 (5.18)
Wet	0.19 (1.07)	0.17 (0.94)	0.17 (0.95)	0.21 (1.18)	0.21 (1.15)	0.20 (1.15)
Wild	1.85 (3.45)	1.82 (3.39)	1.81 (3.3)	1.49 (2.80)	1.48 (2.79)	1.46 (2.76)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
Woodland	3.25 (4.54)	3.15 (4.37)	3.15 (4.37)	3.04 (5.26)	3.03 (5.23)	3.00 (5.18)
Habitat diversity						
Habitat richness	9.23 (5.34)	9.13 (5.33)	9.10 (5.31)	8.20 (5.20)	8.22 (5.20)	8.14 (5.17)
Shannon's Index	0.65 (0.55)	0.64 (0.55)	0.63 (0.55)	0.57 (0.52)	0.57 (0.52)	0.56 (0.51)
Simpson's Index	0.28 (0.24)	0.28 (0.24)	0.28 (0.24)	0.25 (0.23)	0.25 (0.23)	0.25 (0.23)
Biodiversity						
Butterfly richness	5.53 (8.84)	5.41 (8.80)	5.36 (8.76)	5.31 (8.23)	5.30 (8.23)	5.19 (8.14)
Bird richness	19.43 (1.26)	18.68 (27.91)	18.62 (27.83)	16.18 (27.98)	16.06 (27.76)	15.63 (27.27)
Plant richness	73.00 (102.12)	70.93 (100.72)	70.66 (100.16)	62.95 (80.47)	63.03 (80.21)	62.42 (79.27)
Total richness	97.96 (128.67)	95.02 (126.89)	94.64 (126.20)	84.43 (106.15)	84.39 (105.71)	83.24 (104.48)
NDVI						
NDVI mean	0.36 (0.10)	0.36 (0.10)	0.36 (0.10)	0.33 (0.10)	0.33 (0.10)	0.33 (0.10)
NDVI standard deviation	0.17 (0.03)	0.17 (0.03)	0.17 (0.03)	0.17 (0.03)	0.17 (0.03)	0.16 (0.03)
Distance-decay variables						
Distance	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.02 (0.48)	0.02 (0.48)	0.02 (0.46)
Area	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)	0.07 (1.91)	0.07 (1.89)	0.07 (1.82)
Habitat types						
ACDG (Acid grassland)	6.13 (91.33)	5.92 (87.31)	5.99 (87.84)	3.89 (137.68)	4.00 (143.80)	5.12 (172.48)
ALTA (Allotments)	1.84 (32.27)	1.74 (30.75)	1.64 (29.72)	1.83 (51.90)	1.80 (51.26)	2.29 (67.79)
AMNG (Amenity grassland)	14.83 (92.39)	14.81 (97.65)	14.53 (93.64)	61.25 (1620.43)	59.90 (1599.40)	61.45 (1510.76)
ARBL (Arable)	3.33 (32.14)	2.65 (26.41)	2.59 (26.02)	6.25 (221.12)	6.14 (218.40)	6.12 (216.93)
BASG (Chalk grassland)	0.96 (10.40)	1.46 (46.54)	1.46 (47.42)	0.53 (11.92)	0.60 (13.31)	0.57 (12.72)
BATH (Bare artificial)	3.59 (23.72)	4.16 (41.40)	4.20 (41.88)	24.81 (535.36)	24.22 (527.83)	23.56 (490.81)
BOGG (Bog)	0.00 (0.01)	0.00 (0.03)	0.00 (0.03)	0.02 (1.28)	0.02 (1.15)	0.02 (1.35)
BRAK (Bracken)	0.17 (1.06)	0.17 (1.07)	0.17 (1.09)	0.24 (4.75)	0.24 (4.61)	0.23 (4.56)
BSAR (Bare ground)	1.48 (17.37)	1.57 (18.95)	1.58 (19.19)	17.21 (917.00)	16.71 (905.09)	14.57 (834.97)
CONW (Conifer woodland)	0.09 (0.94)	0.11 (1.05)	0.11 (1.06)	0.22 (5.67)	0.23 (5.72)	0.21 (5.34)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
DTWF (Ditch)	0.42 (6.48)	0.40 (6.16)	0.41 (6.20)	0.55 (21.13)	0.54 (20.85)	0.47 (19.24)
FNCR (Carr)	0.18 (4.25)	0.14 (3.51)	0.14 (3.54)	0.03 (0.66)	0.03 (0.65)	0.03 (0.63)
HINA (Not available)	0.08 (0.28)	0.08 (0.24)	0.08 (0.25)	0.22 (3.59)	0.22 (3.56)	0.21 (3.39)
HTHL (Heathland)	0.09 (1.92)	0.09 (1.93)	0.09 (1.97)	0.09 (2.57)	0.09 (2.56)	0.08 (2.42)
IMSS (Imp grassland)	0.10 (0.95)	0.01 (0.06)	0.09 (0.78)	0.35 (9.49)	0.34 (9.37)	0.33 (9.26)
IRAG (Imp-agri grassland)	3.72 (42.96)	3.63 (43.57)	3.52 (42.14)	8.26 (204.58)	8.42 (204.09)	7.91 (189.33)
NHRG (Herb rich grassland)	1.23 (13.44)	1.12 (11.21)	1.12 (11.38)	3.03 (75.99)	2.96 (75.02)	3.09 (77.26)
NNBW (Non-native woodland)	2.73 (63.71)	1.92 (50.30)	1.97 (51.33)	30.99 (1148.67)	30.40 (1134.21)	29.77 (1103.92)
NNHD (Non-native hedge)	0.08 (0.57)	0.07 (0.50)	0.07 (0.49)	0.13 (1.81)	0.12 (1.72)	0.13 (1.70)
NSIG (Semi-imp grassland)	7.60 (34.42)	7.48 (34.28)	7.28 (33.24)	29.57 (407.29)	29.79 (404.73)	28.91 (393.98)
NTSV (Not surveyed)	0.70 (8.41)	0.65 (7.05)	0.65 (7.15)	2.26 (95.13)	2.20 (5.67)	2.13 (87.09)
NVBW (Native woodland)	13.09 (237.26)	10.57 (189.64)	10.57 (193.00)	36.63 (939.89)	37.80 (979.60)	35.52 (914.60)
NVHD (Native hedge)	0.51 (2.78)	0.48 (2.45)	0.47 (2.43)	1.70 (33.62)	1.76 (35.88)	1.79 (35.16)
NWAS (Woodland & scrub)	0.00 (0.14)	0.00 (0.22)	0.00 (0.23)	0.05 (1.98)	0.04 (1.80)	0.05 (1.82)
ORCH (Orchard)	0.15 (5.21)	0.12 (4.50)	0.12 (4.60)	0.03 (0.81)	0.04 (0.91)	0.04 (0.90)
OTHR (Other)	0.10 (0.35)	0.19 (9.46)	0.27 (13.65)	7.93 (495.43)	7.71 (489.05)	6.72 (451.12)
PLSH (Shrubbery)	0.49 (2.59)	0.53 (3.52)	0.56 (3.92)	2.19 (86.85)	2.41 (98.27)	2.50 (92.76)
RDEP (Ruderal)	1.07 (8.20)	1.32 (13.45)	1.33 (13.68)	24.76 (1442.63)	23.96 (1423.89)	20.80 (1313.48)
RDSW (Reed)	0.07 (0.51)	0.09 (0.61)	0.09 (0.61)	0.37 (9.44)	0.36 (9.32)	0.36 (9.28)
RGHL (Roughland)	1.50 (13.77)	1.55 (13.45)	1.58 (13.67)	7.12 (199.55)	7.06 (197.19)	6.73 (186.16)
RWRS (River)	0.75 (5.03)	0.69 (4.24)	0.70 (4.35)	2.07 (76.49)	2.02 (75.52)	1.89 (70.68)
SCRB (Scrub)	7.57 (108.62)	6.36 (92.44)	6.28 (91.45)	44.16 (1526.28)	43.78 (1507.66)	41.58 (1465.25)
SCTR (Scat trees)	4.74 (37.26)	4.74 (36.55)	4.68 (36.01)	10.73 (157.84)	11.02 (165.79)	11.09 (158.00)
STMS (Saltmarsh)	0.01 (0.12)	0.01 (0.11)	0.01 (0.11)	0.02 (0.55)	0.02 (0.50)	0.02 (0.51)
STWC (Still water)	2.01 (15.41)	1.97 (15.19)	1.92 (14.81)	26.82 (1150.01)	26.12 (1135.40)	26.13 (1124.87)
TLHB (Tall herb)	1.88 (15.91)	1.83 (14.78)	1.78 (14.36)	29.66 (844.30)	28.99 (833.54)	26.96 (802.87)
TYSW (Swamp)	0.08 (0.83)	0.07 (0.72)	0.07 (0.73)	0.23 (6.11)	0.23 (6.04)	0.24 (6.18)
VEGW (Vegetated walls)	0.05 (0.38)	0.04 (0.33)	0.04 (0.33)	0.26 (16.94)	0.31 (19.21)	0.30 (18.08)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
WOOD (Woodland)	0.02 (0.25)	0.02 (0.20)	0.02 (0.20)	0.09 (3.02)	0.08 (2.69)	0.09 (3.29)
WTMV (Wet marginal)	0.11 (0.66)	0.12 (0.72)	0.12 (0.73)	1.36 (38.58)	1.33 (38.09)	1.34 (38.57)
Habitat categories						
Grassland	34.47 (167.96)	34.42 (176.3)	33.92 (172.27)	106.52 (1744.99)	105.67 (1724.35)	107.05 (1655.81)
Maintained	17.79 (99.19)	17.72 (104.81)	17.41 (100.50)	94.93 (1842.80)	93.18 (1820.19)	92.82 (1728.21)
Use	20.19 (103.84)	19.37 (106.20)	18.92 (102.07)	69.63 (1638.91)	68.19 (1617.69)	70.20 (1531.04)
Water	2.75 (16.61)	2.65 (16.27)	2.62 (15.94)	28.88 (1158.29)	28.14 (1143.50)	28.02 (1132.12)
Wet	0.79 (6.98)	0.78 (6.65)	0.79 (6.69)	2.90 (63.39)	2.82 (62.58)	2.78 (62.10)
Wild	10.76 (118.10)	9.82 (101.83)	9.78 (101.06)	78.01 (2262.40)	76.73 (2233.00)	71.06 (2111.91)
Woodland	20.68 (305.88)	17.37 (245.66)	17.36 (249.83)	78.70 (1776.58)	79.57 (1785.17)	76.72 (1715.63)
Habitat diversity						
Habitat richness	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.02 (0.61)	0.02 (0.60)	0.02 (0.58)
Shannon's Index	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.15)	0.00 (0.15)	0.00 (0.14)
Simpson's Index	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.08)	0.00 (0.08)	0.00 (0.08)
Biodiversity						
Butterfly richness	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.13)	0.01 (0.13)	0.01 (0.13)
Bird richness	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.01 (0.22)	0.01 (0.21)	0.01 (0.20)
Plant richness	0.01 (0.06)	0.01 (0.06)	0.01 (0.06)	0.05 (0.88)	0.05 (0.88)	0.05 (0.82)
Total species richness	0.02 (0.06)	0.02 (0.07)	0.02 (0.07)	0.06 (0.96)	0.07 (0.96)	0.06 (0.90)
NDVI						
NDVI mean	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.24)	0.01 (0.24)	0.01 (0.23)
NDVI standard deviation	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.10)	0.00 (0.10)	0.00 (0.09)
Spatial control variables						
Income deprivation	0.16 (0.10)	0.16 (0.01)	0.16 (0.01)	0.22 (0.12)	0.22 (0.12)	0.22 (0.13)
Employment deprivation	0.09 (0.04)	0.09 (0.04)	0.09 (0.04)	0.10 (0.05)	0.10 (0.05)	0.11 (0.05)
Education deprivation	13.50 (10.60)	13.63 (10.68)	13.70 (10.69)	15.44 (10.41)	15.49 (10.41)	15.85 (10.46)
Crime deprivation	0.34 (0.60)	0.35 (0.59)	0.35 (0.59)	0.48 (0.57)	0.48 (0.57)	0.49 (0.56)
NO_2	34.66 (3.83)	34.76 (6.60)	34.79 (6.60)	28.87 (7.01)	28.89 (6.99)	29.23 (7.09)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
Age (yrs)						
16-25	16.17%	17.26%	17.28%	18.03%	18.27%	17.79%
26-35	20.47%	21.58%	21.40%	18.71%	18.83%	19.15%
36-45	18.80%	18.46%	18.38%	21.27%	21.27%	21.46%
46-55	15.85%	16.00%	15.95%	18.26%	18.22%	18.12%
56-65	13.46%	12.39%	12.36%	11.73%	11.59%	11.43%
66-75	9.02%	8.31%	8.33%	7.97%	7.82%	7.83%
75+	6.23%	6.00%	6.30%	4.03%	4.00%	4.22%
University-level qualification	30.65%	28.34%	28.01%	47.82%	47.88%	45.80%
In a relationship	58.79%	58.48%	58.36%	55.16%	54.84%	55.37%
Living with children	23.11%	24.01%	23.97%	31.61%	31.64%	32.50%
Annual household income	7.32 (0.84)	7.19 (0.84)	7.18 (0.84)	7.44 (0.69)	7.44 (0.70)	7.40 (0.71)
Health condition	16.08%	16.35%	16.51%	26.48%	26.22%	26.37%
Employment status						
Employed	62.29%	61.28%	60.83%	57.26%	57.38%	55.51%
Unemployed	6.32%	7.01%	7.00%	9.91%	9.99%	10.75%
Retired	17.45%	16.42%	16.62%	13.78%	13.58%	13.76%
Caring for family	7.21%	8.01%	8.21%	7.92%	7.82%	8.95%
In training	6.18%	6.84%	6.91%	10.45%	10.56%	10.37%
Other	0.55%	0.44%	0.43%	0.68%	0.67%	0.66%
House type						
Detached	7.63%	6.93%	6.84%	-	-	-
Semi-detached	25.30%	25.77%	25.70%	-	-	-
Terraced	36.31%	35.19%	34.99%	-	-	-
Flat	29.24%	30.77%	31.09%	-	-	-
Other	1.52%	1.34%	1.38%	-	-	-
Household space						
<1 room per person	6.79%	7.31%	7.32%	16.01%	16.07%	17.53%

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	BHPS	BHPS	BHPS	UKHLS	UKHLS	UKHLS
	Mean (St. Dev.) or % N=8,469	Mean (St. Dev.) or % N=13,622	Mean (St. Dev.) or % N=13,077	Mean (St. Dev.) or % N=34,061	Mean (St. Dev.) or % N=34,947	Mean (St. Dev.) or % N=41,087
1 - < 3 rooms per person	76.35%	77.36%	77.39%	70.61%	70.59%	69.66%
3 ≥ rooms per person	16.86%	15.33%	15.29%	13.38%	13.34%	12.81%
Commuting time						
None	40.27%	41.11%	41.58%	46.86%	46.82%	48.55%
≤ 15 mins	15.92%	16.21%	16.06%	11.15%	11.13%	10.80%
16-30 mins	16.98%	16.95%	16.67%	15.06%	15.05%	14.63%
31-50 mins	12.81%	12.54%	12.64%	13.04%	13.04%	12.65%
≥ 50 mins	14.02%	13.19%	13.05%	13.89%	13.96%	13.37%
Other						
Wave	11.38 (3.83)	6.63 (5.03)	8.60 (5.20)	22.34 (2.35)	22.37 (2.33)	22.09 (2.33)

5.3.8 Exposure measurement

LSOA-level

The proportion of habitat types, habitat diversity, biodiversity and NDVI (mean and standard deviation) were calculated for all LSOAs in Greater London. These metrics were then linked to every individual in the BHPS and UKHLS for each wave based on residential LSOA, creating a longitudinal dataset of neighbourhood biodiversity for every participant in the sample.

Distance-decay

The proportion of habitat types, habitat diversity, habitat categories, biodiversity and NDVI (mean and standard deviation) were calculated for all OSSs in Greater London. We then constructed distance-decay functions for each measure of habitat, biodiversity and NDVI to estimate exposure to biodiversity:

$$E = \sum_{i=1}^{n} \left(\frac{B}{d^2}\right)_i$$

Where E is the exposure score, B refers to the measure of biodiversity, d is the distance from the residential postcode to the nearest edge of an OSS (*i*), and n is the number of OSSs in Greater London. For calculating the exposure to size of OSS only, we used the $\log_{10}$ transformation of area. For calculating the exposure to each habitat type, we used the total area of each type in each OSS rather than proportion. For calculating the exposure to the habitat richness and species richness metrics, we added 1 to each category to avoid the effect of zeros in the function. For calculating the exposure to the habitat diversity and biodiversity metrics, we divided the metric by the $\log_{10}$ area of the OSS. This accounts for the positive relationship between diversity and site area. If the distance value was equal to zero (i.e. the residential postcode centroid fell inside an OSS), we converted it to 10 to avoid the effect of zeroes in the function.

The distance-decay functions were run for each unique residential location in both the BHPS (1691 locations) and UKHLS (9110 locations) samples. This created a set of exposure scores to each measure of biodiversity for each location in our samples. These exposure scores were then assigned to every individual in our two population samples linked by their geographical location for each wave, creating a longitudinal dataset of exposure to biodiversity for every participant in the sample.

5.3.9 Statistical analysis

We linked the neighbourhood-level variables to each individual by LSOA code for each wave (NO_2 and deprivation). We then constructed regression models to examine the relationship between subjective wellbeing and either neighbourhood biodiversity or exposure to all OSSs. We built six model specifications (Table 5.5) and applied these to both the LSOA-level and distance-decay analyses, for each biodiversity metric.

Table 5.5. The six model specifications used in this study, ran for each habitat type, habitat category, habitat diversity metric, biodiversity metric, and NDVI (mean and standard deviation).

Model		Dependent variable	Model specification
1	BHPS	Life satisfaction	Habitat/biodiversity metric + control variables
2		GHQ	
3		General health	
4	UKHLS	GHQ	Habitat/biodiversity metric + control variables
5		Life satisfaction	
6		General health	

We constructed the model equation using fixed effects regression:

$$SW_{ijt} = \beta_0 + \beta_1 A_{jt} + \beta_2 L_{jt} + \beta_3 X_{it} + \beta_4 T_t + \varepsilon_{ijt}$$

Where SW is a measure of subjective well-being (life satisfaction, GHQ or general health), for an individual *i*, at a given location *j* and in a given year *t*. It is a function of a habitat/biodiversity exposure metric (A_{jt}), a vector of LSOA neighbourhood factors (L_{jt}) and individuals' socio-economic and demographic characteristics (X_{it}), and a wave variable (T_t). ε_{ijt} is the error term (all remaining unaccounted for variation).

All analyses were carried out in the UK Data Service Secure Lab environment. Spatial analyses were performed in R v3.5.2 (R Core Team 2020) using the rgeos package, and in ArcGIS v10 (ESRI 2011). Regression analysis was performed using the xt suites in Stata 16 software (StataCorp 2019).

To test for correlation between our measures of habitat diversity and biodiversity within OSSs, we carried out pairwise Spearman rank correlation tests. To determine if habitat diversity and biodiversity differed across different types of green- and bluespace, we conducted a Kruskal-Wallis H test to compare diversity metrics across the Planning Policy Guidance 17 (PPG17) categories. The Planning Policy Guidance Note 17 (PPG17): *Planning for open space, sports and recreation* is a formal open space typology for land use planning guidance used by UK government and local authorities to design and assess its land use strategy (Office of the Deputy Prime Minister 2002). The PPG17 consists of 11 land use categories, including Parks and gardens, Natural and semi-natural urban greenspace, Cemeteries and churchyards and Outdoor sports facilities, and each OSS site has a PPG17 designation.

5.4 Results

5.4.1 Habitat types

LSOA-level analysis

We provide summarised regression results in Table 5.6 (see Tables S5.2 and S5.3 in appendix for full regression results, and Tables S5.4 and S5.5 in appendix for standardised coefficients). In the LSOA-level analysis for the BHPS, we find positive relationships between subjective well-being and Allotments (life satisfaction: b=0.042, β=0.100, p=0.007; GHQ: b=-0.144, β=-0.079, p=0.015), Ditch (life satisfaction b=1.816, β=0.090, p<0.001), Carr (general health: b=0.434, β=0.029, p=0.018), Orchard (general health: b=0.296, β=0.039, p=0.013), and Vegetated walls (GHQ: b=-0.190, β=-0.026, p=0.007). We find a negative significant relationship with Intertidal (life satisfaction: b=-0.063, β=-0.039, p=0.047), Non-native woodland (life satisfaction: b=-0.044, β=-0.045, p=0.012), and Woodland & scrub (GHQ: b=1.325, β=0.016, p=0.043). The only habitat type to have a significant association with more than one of the three measures of well-being is Allotments; we find a significant positive association here with both life satisfaction and mental health.

In the LSOA-level analysis for the UKHLS, we find positive associations between at least one subjective well-being measure and Bare artificial (life satisfaction: b=0.010, β=0.033, p=0.030), Improved-agricultural grassland (GHQ: b=-0.065 β=-0.027, p=0.037), Herb-rich grassland (life satisfaction: b=0.040, β=0.030, p=0.048; GHQ: b=-0.205, β=-0.042, p=0.007; general health b=0.021, β=0.022, p=0.037), Other (life satisfaction: b=0.054, β=0.026, p=0.029) and Still water (life satisfaction: b=0.024, β=0.056, p<0.001; GHQ: b=-0.057, β=-0.035, p=0.014). We find negative significant relationships with Conifer woodland (life satisfaction: b=-0.214, β=-0.035, p=0.029), Swamp (general health: b=-0.314, β=-0.088, p=0.005), and Wet marginal (GHQ: b=0.748, β=0.028, p=0.043). The habitat types that have a significant association with more than one of the three measures of well-being are Herb-rich grassland and Still water, we find a significant positive association here with life satisfaction, mental health and general health, and mental health and general health respectively.

Table 5.6. Summary table of regression results. Blue cells indicate a significant positive relationship, red cells indicate a significant negative relationship. LS = Life satisfaction, GHQ = General Health Questionnaire, GH = General health.

	LSOA						Distance decay					
	BHPS			UKHLS			BHPS			UKHLS		
Habitat types	LS	GHQ	GH	LS	GHQ	GH	LS	GHQ	GH	LS	GHQ	GH
Acid grassland												
Allotments												
Amenity grassland												
Arable												
Chalk grassland												
Bare artificial												
Bogg												
Bracken												
Bare ground												
Conifer woodland												
Ditch												
Carr												
Not available												
Heath												
Intertidal												
Imp-agri grassland												
Herb-rich grassland												
Non-native woodland												
Non-native hedge												
Semi-impr grassland												
Not surveyed												
Native woodland												
Native hedge												
Woodland & scrub												
Orchard												
Other												
Shrubbery												
Ruderal												
Reed												
Roughland												
River												
Scrub												
Scat trees												
Saltmarsh												
Still water												
Tall herb												
Swamp												
Vegetated walls												
Woodland												
Wet marginal												
Habitat categories												
Grassland												
Maintained												

Use												
Water												
Wet												
Wild												
Woodland												
Habitat diversity												
Habitat richness												
Shannon’s Index												
Simpson’s Index												
Biodiversity												
Butterfly richness												
Bird richness												
Plant richness												
Total species richness												
NDVI												
NDVI mean												
NDVI stdev.												

Distance-decay analysis

In the distance-decay analysis for the BHPS, we find a positive relationship between life satisfaction and Other (b=0.116, β=0.032, p=0.006). We find negative significant relationships with Arable (general health: b=-0.001, β=-0.026, p=0.022), Bare artificial (life satisfaction: b=-0.002, β=-0.035, p=0.040), Bare ground (GHQ: b=0.010, β=0.035, p=0.016; general health: b=-0.002, β=-0.037, p=0.006), Carr (GHQ: b=0.031, β=0.020, p=0.048; general health: b=-0.008, β=-0.031, p=0.001), Herb-rich grassland (GHQ: b=0.012, β=0.025, p=0.020; general health: b=-0.002, β=-0.031, p=0.002), Non-native woodland (GHQ: b=0.003, β=0.025, p=0.013; general health: b=-0.001, β=-0.030, p=0.001), Native woodland (GHQ: b=0.001, β=0.025, p=0.014; general health: b=-0.000, β=-0.031, p=0.001), Ruderal (general health: b=-0.004, β=-0.054, p=0.006), Roughland (GHQ: b=0.011, β=0.027, p=0.031), Scrub (GHQ: b=0.002, β=0.037, p=0.030; general health: b=-0.000, β=-0.046, p=0.003), and Saltmarsh (general health: b=-0.210, β=-0.040, p=0.040). The habitat types to have a significant association with more than one of the three measures of well-being are Bare ground, Carr, Herb-rich grassland, Non-native woodland, Native woodland, and Scrub, we find significant negative associations here with both mental health and general health for all of them.

In the distance-decay analysis for the UKHLS, we find a positive relationship between subjective well-being and Conifer woodland (life satisfaction: b=0.006, β=0.024, p=0.001; GHQ: b=-0.016, β=-0.016, p=0.020). We find negative significant relationships with Allotments (general health: b=-0.001, β=-0.033, p=0.016), Arable (life satisfaction: b=-0.001, β=-0.156, p=0.035), Ditch (life satisfaction: b=-0.004, β=-0.060, p<0.001), Carr (GHQ: b=0.349, β=0.040, p=0.009), Improved-agri grassland (life satisfaction: b=-0.001, β=-0.135, p=0.012), Not surveyed (general health: b=-0.000, β=-0.010, p=0.024), Woodland & scrub (life satisfaction: b=-0.031, β=-0.040, p=0.025), Shrubbery (GHQ: b=0.012, β=0.202, p=0.032; general health: b=-0.002, β=-0.194, p=0.001), River (b=-0.001, β=-0.045, p=0.001), and Saltmarsh (life satisfaction: b=-0.111, β=-0.040, p=0.025). The habitat types to have a significant association with more than one of the three measures of well-being are Conifer woodland and Shrubbery, we find a significant positive association here with both life satisfaction and mental health, and mental health and general health respectively.

5.4.2 Habitat diversity

We find no associations between subjective well-being and habitat diversity across all the models.

5.4.3 Biodiversity

In the LSOA analysis with the BHPS, we find a positive and significant relationship between general health and both butterfly species richness (b=0.004, β=0.042, p=0.043) and bird species richness (b=0.001, β=0.034, p=0.034), but no association with, plant or total richness. We find no other significant associations across our models.

5.4.4 NDVI

In the UKHLS LSOA analyses, we find a significant positive association between general health and both NDVI mean and standard deviation (mean: b=0.324, β=0.031, p=0.028; standard deviation: b=1.014, β=0.026, p=0.021). We find no other significant relationships across our models.

5.4.5 New habitat categories

In the LSOA analysis, we find a significant positive association between life satisfaction and Water (b=0.012, β=0.041, p=0.005) in the UKHLS. In the distance-decay analysis, we find a significant negative relationship with Wild (GHQ: b=0.002, β=0.041, p=0.012; general health: b=-0.000, β=-0.044, p=0.002) and Woodland (GHQ: b=0.001, β=0.025, p=0.014: general health: b=-0.000, β=-0.032, p=0.001) with the BHPS, and with Wet and life satisfaction (b=0.001, β=-0.046, p=0.013) in the UKHLS.

5.4.6 LSOA vs Distance-decay

We find two habitat types with significant associations with subjective well-being in the same direction in both the LSOA and distance-decay analysis: Non-native woodland (negative in both BHPS results) and Woodland & scrub (negative in UKHLS distance-decay and BHPS LSOA). Seven other habitat types have significant relationships in both analyses but have opposing directions (Allotments, Bare artificial, Conifer woodland, Ditch, Carr, Imp-agri grassland and Herb-rich grassland).

5.4.7 Relationships between measures of habitat diversity and biodiversity

To test for correlation between our measures of habitat diversity and biodiversity within OSSs, we carried out pairwise Spearman rank correlation tests (Table 5.7). The procedure described by Benjamini and Hochberg was used to correct p-values for multiple testing (Benjamini & Hochberg 1995). We found strong positive correlations between all three measures of habitat diversity (richness, Shannon's index, and Simpson's index). Total species richness was strongly and positively correlated with both bird richness and plant richness (this was expected by design), and site area. Mean NDVI 2000 was strongly and positively correlated with mean NDVI 2018, however NDVI standard deviation 2000 and 2018 were not strongly correlated.

Table 5.7. Spearman rank correlation matrix of habitat and biodiversity scores for Open Space Sites (OSSs), rs values (p<0.001 for all cells, before and after adjustment; strong correlations in bold).

	Area	Habitat richness	Habitat Shannon's	Habitat Simpson's	Butterfly richness	Bird richness	Plant richness	Total richness	NDVI 2000 mean	NDVI 2000 stdev	NDVI 2018 mean	NDVI 2018 stdev
Area	1											
Habitat richness	0.579	1										
Habitat Shannon's	0.404	**0.771**	1									
Habitat Simpson's	0.360	**0.714**	**0.987**	1								
Butterfly richness	0.488	0.437	0.339	0.301	1							
Bird richness	0.548	0.476	0.405	0.369	0.552	1						
Plant richness	0.568	0.609	0.568	0.533	0.542	0.636	1					
Total richness	**0.610**	0.624	0.572	0.536	0.594	**0.719**	**0.979**	1				
NDVI 2000 mean	0.553	0.379	0.223	0.197	0.336	0.349	0.376	0.399	1			
NDVI 2000 stdev	0.418	0.299	0.311	0.306	0.153	0.234	0.263	0.280	0.029	1		
NDVI 2018 mean	0.402	0.345	0.258	0.242	0.311	0.343	0.382	0.399	**0.760**	0.068	1	
NDVI 2018 stdev	0.189	0.173	0.244	0.248	0.023	0.075	0.109	0.115	-0.185	0.503	-0.229	1

5.4.8 Ecological characteristics of Planning Policy Guidance 17 (PPG17) categories

A Kruskal-Wallis H test was conducted to determine if habitat and biodiversity differed across OSS Planning Policy Guidance 17 (PPG17) categories. All OSS sites that did not contain any habitat or biodiversity data were removed from this analysis. The tests showed that there were significant differences in the rank sum of means of all habitat and biodiversity measures between the 11 PPG17 categories (Table 5.8). The data distributions can be seen in boxplots (see Figures S5.8, S5.9, S5.10, S5.11, S5.12, S5.13, S5.14, S5.15, S5.16 and S5.17 in the appendix).

The highest mean species richness values are found for the Natural and semi-natural urban greenspace category but this category also has the largest inter-quartile range. The graphs show the positive skew of the species richness data, with many outliers above the mean. The highest mean habitat richness values are also found for the Natural and semi-natural urban greenspace category but this category also has the largest inter-quartile range. We find a clear difference in mean NDVI score between Natural and semi-natural urban greenspace and all other categories, apart from Other urban fringe. Civic spaces have the lowest mean NDVI score. The categories with the lowest NDVI standard deviation mean were Allotments, Community Gardens and City Farms, Natural and Semi-natural Urban Greenspaces and Civic Spaces.

Table 5.8. Cell counts of the Kruskal-Wallis tests between habitat and biodiversity metrics across the 11 Open Space Sites (OSSs) Planning Policy Guidance 17 categories (PPG17).

	Cell counts (N)									
PPG17 category	Butterfly richness	Bird richness	Plant richness	Habitat richness	Habitat Shannon's	Habitat Simpson's	NDVI mean 2000	NDVI stdev 2000	NDVI mean 2018	NDVI stdev 2018
Allotments, Community Gardens and City Farms	210	286	463	649	649	649	776	776	776	776
Amenity	455	1,121	2,065	2,937	2,937	2,937	3,803	3,803	3,803	3,803
Cemeteries and Churchyards	148	241	286	367	367	367	430	430	430	430
Children and Teenagers	17	28	70	118	118	118	257	257	257	257
Civic Space	12	34	34	72	72	72	221	221	221	221
Green Corridors	356	581	1,063	1,263	1,263	1,263	1,563	1,563	1,563	1,563
Natural and Semi-natural Urban Greenspace	429	551	655	720	720	720	741	741	741	741
Other	188	314	554	667	667	667	692	692	692	692
Other Urban Fringe	351	528	722	791	791	791	797	797	797	797
Outdoor Sports Facilities	435	732	1,033	1,240	1,240	1,240	1,394	1,394	1,394	1,394
Parks and Gardens	511	926	1,136	1,314	1,314	1,314	1,532	1,532	1,532	1,532
Test statistics										
Kruskal-Wallis H	219.809	605.247	826.147	419.395	605.970	742.405	3119.624	609.662	3201.223	1325.144
p-value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

5.5 Discussion

Our study examined the relationship between subjective well-being and measures of habitat and biodiversity. We calculated metrics of habitat type and diversity, species richness and NDVI (mean and standard deviation) to assess the association with three measures of subjective well-being. We used adult population samples from two large panel surveys (BHPS and UKHLS) in Greater London and applied two different methods to capture residential exposure to the natural environment: LSOA-level statistics and distance-decay functions from individuals' residence to all Open Space Sites (OSSs).

We find that habitat diversity is not important for well-being, but that particular habitat types are, supporting previous work that suggests the same (Olsen *et al.* 2019). We find several signals of positive and negative relationships between habitat types and subjective well-being. For example, we find several positive associations between well-being and Allotments, Herb-rich grassland and Still water. We also find several negative associations between well-being and Native and Non-native broadleaf woodland, Bare ground and Scrub.

We find some evidence for a positive relationship between biodiversity and well-being. We find a small positive association between self-reported general health and butterfly and bird species richness, and NDVI (mean and standard deviation). Our results suggest that in our London samples, neighbourhood proportions of biodiversity might be significant predictors of individual-level subjective well-being, supporting the findings from previous reviews of biodiversity and health and well-being literature that find weak evidence to suggest more ecologically diverse locations are associated with health and well-being benefits (Lovell *et al.* 2014), and is one of the few studies that examines this relationship within the residential context.

However, there is very little consistency across our survey samples, subjective well-being measures, and between the two analysis methods used. For example, in the LSOA-level analysis, we find positive significant relationships between all three subjective well-being measures and Herb-rich grassland in the UKHLS, but no relationships in the BHPS. When using the distance-decay method, we find *negative* significant relationships with two subjective well-being measures and Herb-rich grassland in the BHPS, and no relationship in the UKHLS. These findings suggest important differences in how individual well-being is related to habitat and biodiversity, between population samples and exposure methods.

5.5.1 Are there particular habitats that are associated with subjective well-being?

We find several significant positive relationships between habitat types and subjective well-being. In the LSOA-level analysis, we find significant positive relationships with two or more measures of subjective well-being for Allotments, Herb-rich grassland and Still water. We find significant positive relationships with one measure of well-being in the LSOA analysis with the BHPS and Ditch, Carr, Orchard, and Vegetated walls, and with the UKHLS in Bare artificial, Improved-agri grassland and Other. In the distance-decay analysis, we find significant positive relationships with two measures of subjective well-being for Conifer woodland using the UKHLS. We find a significant positive relationship between one measure of subjective well-being in the BHPS with life satisfaction and Other. These findings support our current understanding about the well-being benefits of allotments (van den Berg *et al.* 2010b), bluespaces (Garrett *et al.* 2019b; Gascon *et al.* 2017; Jarvis *et al.* 2020b) and woodland (Tyrväinen *et al.* 2014; Wheeler *et al.* 2015). Our findings regarding the two grassland categories suggest that urban grassland that is species-rich or associated with agricultural use may be important for well-being, also found in other studies (Jarvis *et al.* 2020b). The habitat types Ditch and Carr are often likely to contain still water, which may explain the positive relationship found here too. Orchards are suggestive of food provision and community use, and Vegetated walls may be aesthetically appealing, both possible explanations for the positive relationships found. The positive associations with the Other type suggest there may be important habitats undisclosed in this category.

We also find several significant negative relationships between habitat types and subjective well-being. In the LSOA analysis, we do not find any habitat types with a significant negative relationship with two or more habitat types. We find a significant negative relationship with one measure of well-being for Intertidal, Non-native broadleaf woodland and Woodland and scrub in the BHPS, and with Conifer woodland, Swamp and Wet marginal in the UKHLS. These negative findings relating to both non-native broadleaf and conifer woodland types are surprising given other research suggesting residential exposure to woodland (Wheeler *et al.* 2015) and conducting activities in woodlands is beneficial for well-being (O'Brien *et al.* 2014; Ojala *et al.* 2019). However, Wheeler et al., (2015) found differential associations with Conifer woodland by income deprivation decile as well as level of urbanity, which might explain the contradictory findings here. Additionally, previous qualitative studies have found that urban woodlands can also be perceived as unsafe (Milligan & Bingley 2007b). The negative findings with semi-wet habitats such as Swamp, Intertidal and Wet marginal may also be similarly attributed to feelings of being unsafe.

In the distance-decay analysis, using the BHPS, we find many significant negative relationships between habitat types and with two or more measures of well-being. These are found with Bare ground, Carr, Herb-rich grassland, Non-native woodland, Native woodland, and Scrub, and are for mental health and general health in all cases. We also find significant negative relationships with one measure of well-being for Arable, Bare artificial, Ruderal, Roughland and Saltmarsh. With the UKHLS, we find a significant negative relationship between Shrubbery and two subjective well-being measures, and between Allotments, Arable, Ditch, Carr, Improved-agri grassland, Not surveyed, Woodland and scrub, River, and Saltmarsh and one measure of subjective well-being in the UKHLS. These many negative relationships between well-being and habitat types in the distance-decay analysis indicate that close proximity to these habitat types are associated with lower levels of well-being. Previous work has found similar negative relationships between well-being and saltwater environments such as saltmarshes and intertidal (Alcock *et al.* 2015). However, these negative associations contradict previous studies that find positive associations between habitat types and well-being, such as that found with arable (Olsen *et al.* 2019), woodlands and grasslands (MacKerron & Mourato 2013; Wheeler *et al.* 2015), and saltmarshes (Rendón *et al.* 2019).

When we compare our findings across both the BHPS and UKHLS in the distance-decay analyses, we find significant relationships between subjective well-being and Arable, Carr, Saltmarsh and the new Woodland category in both surveys. There are no such findings in the LSOA analysis. This might indicate important differences between the exposure methods in how they represent the underlying differences in the two population samples. The LSOA method only accounts for exposure to habitats within the LSOA, and excludes anything beyond that. As the distance-decay method includes exposure to all habitats, it might better account for the differences in spatial structure between the BHPS and UKHLS. The sampling design of the BHPS means individuals in the sample are more spatially clustered than those in the UKHLS. Both surveys have a clustered and stratified sampling design in their main sample for England, but the BHPS participants are drawn from 250 primary sampling units, in contrast to over 3000 in the UKHLS. Therefore there may be fewer individuals with these habitat types in their surrounding neighbourhoods, therefore capturing different sets of neighbourhood habitats to the UKHLS. Therefore, the distance-decay method may be a more suitable method to estimate exposure.

The unstandardised coefficients (b) represent the change in subjective well-being (on the specific scale of life satisfaction, GHQ, or general health) due to a 1% increase in the habitat type in the LSOA or OSS. Using standardised coefficients (β) we can compare the effect sizes within and across models. Standardised coefficients relate to the 1 standard deviation change in subjective well-being with a 1 standard deviation increase in the percentage increase in habitat type in the LSOA or OSS. In the LSOA analysis, the magnitude of the effect sizes of the significant habitat types range from β=±0.016 to 0.100, which suggests that the associations between these types and subjective well-being are comparable, with the positive effect of Allotments with life satisfaction being twice that of Still water and three times that of Herb-rich grassland. Similarly, in the distance-decay analysis the magnitude of the effect sizes of the significant habitat types range from β=±0.016 to 0.202. Many of the effect sizes between the two methods are relatively similar, although the distance-decay method results in several larger coefficients (Shubbery and GHQ in the UKHLS: β=0.202).

Using standardised coefficients also allows us to compare the effect sizes with other determinants of well-being. For example, in the BHPS analysis, we find the positive effect size of a 1 standard deviation increase in Allotments in the LSOA on mental health is approximately twice that of the negative effect found from being unemployed (β = 0.047; when compared to being employed). Similarly in the UKHLS analysis, we find the positive effect size of a 1 standard deviation increase in Still water in the LSOA on life satisfaction is approximately comparable to that of the negative effects found from being unemployed and from having a health condition (β=-0.055 when compared to being employed, and β=-0.043 when compared to being single, respectively). The β coefficients for the control variables are consistent across both population samples and both exposure methods.

To attempt to address issues of small sample sizes in various habitat types (e.g. Woodland & scrub), and to further identify habitat characteristics that may be associated with well-being, we created seven new habitat categories (grassland, maintained, use, water, wet, wild, and woodland). We found some evidence of relationships between these categories and subjective well-being. The positive relationship found with the new Water category in the LSOA analysis with the UKHLS supports previous literature that finds well-being benefits from bluespaces. The negative relationships found with the new Wet and Wild categories suggest that habitats that are relatively changeable, rugged, unmanaged and unmaintained are related to lower levels of well-being, perhaps because they are perceived as unsafe or dangerous. The negative relationships found in the distance-decay analysis between the new Woodland category and two measures of subjective well-being contradicts previous research that finds trees, tree canopy cover and woodlands associated with improved health and well-being . In the individual categories of woodland in the earlier habitat type results, we find mixed results and several negative associations. Perhaps particular woodland categories and/or locations in London are associated with feeling unsafe and isolated (Jansson *et al.* 2013).

5.5.2 Is habitat diversity associated with subjective well-being?

We find very little evidence to suggest any relationship between habitat diversity and subjective well-being. We use three metrics of habitat diversity (richness, Shannon's Index and Inverse Simpson's Index) to capture diversity and find no relationships at all, both within LSOAs and OSSs. These findings are similar to a recent study (Olsen *et al.* 2019) yet different to that found by other studies (Cameron *et al.* 2020; Wheeler *et al.* 2015), who find a relationship between habitat diversity measured by the Shannon's Index. However, Olsen *et al.* (2019) study habitat diversity at the city level, not neighbourhood level, Wheeler et al., (2015) use a different habitat classification in their study (Land Cover Map types), and Cameron et al., (2020) found this relationship with park visitors and not with residential neighbourhoods. It might be that residential diversity or proximity to diverse OSSs do not necessarily relate to the well-being of inhabitants, but do for actual park visitors. It might be that we are capturing a different type of exposure in this study.

Alternatively, it might be that richness is not an adequate measure to capture the relationship between habitats and well-being. Perhaps the combination of particular habitats, such as woodland and water for example, are related to well-being effects. Or maybe habitat types *per se* are less important than the quality of those habitats.

5.5.3 Is biodiversity associated with subjective well-being?

Our findings suggest mixed associations between biodiversity and subjective well-being. We only find two significant relationships between our species richness metrics and well-being across the models (butterfly and bird richness and self-reported general health). The association with bird species richness supports other literature that has also found a similar relationship with bird richness (Cameron *et al.* 2020; Wheeler *et al.* 2015). In urban areas, interaction with wild birds may be the main wildlife experience people have (Cox & Gaston 2016). Urban bird feeding is considered a type of wildlife gardening, and bird song has been found to invoke emotions and memories which may be beneficial for well-being (Ratcliffe *et al.* 2016) The relationship with butterfly species has rarely been found, both Fuller et al., (2007) and Dallimer et al., (2012) found no association between well-being and butterfly species richness, so this is an important finding. Both of these previous studies were conducted in Sheffield, UK, so our positive finding might be specific to London. Alternatively, both of these studies used different measures of subjective well-being to this study, so may have been capturing different relationships between butterfly species richness and well-being.

However, this apparent weak relationship between biodiversity and well-being is also found in previous work that examines this relationship (e.g. Fuller et al., 2007; Luck et al., 2011; Dallimer et al., 2012). One interpretation of these findings is that actual biodiversity is less important for well-being than perceived biodiversity. This has certainly been found in previous studies (Schebella *et al.* 2019), and may indicate that individuals are not able to accurately perceive actual biodiversity levels (Dallimer *et al.* 2012). It seems reasonable to suggest that birds are more easily detected, through sight and sound, whereas butterflies and plants less so. Another suggestion might be that biodiversity levels are related to different measures of health and well-being. For example, Cameron et al., (2020) found an association with momentary happiness, and Luck et al., (2011) found a stronger association with neighbourhood-level well-being than individual well-being.

Alternatively, the weak association found here between biodiversity and well-being may be due to how we chose to measure biodiversity. In this study we chose to use butterfly, bird and plant richness as indicators of biodiversity, in-keeping with previous literature (Lovell *et al.* 2014). Perhaps these taxonomic groups are not important in affecting human well-being, as measured by life satisfaction, GHQ and self-reported general health. Species richness, or the number of species, is just one measure of biodiversity, we have not been able to explore abundance or evenness for example. There may exist an optimum threshold, beyond which higher levels of biodiversity have negative associations with well-being (Lindemann-Matthies

& Matthies 2018). We also did not include other taxonomic groups, such as insects. We have not examined if particular species are important, such as those protected under the BAP designation, or those that are rare or especially noticeable (e.g. colourful or large).

Moreover, the mechanisms for why a more biodiverse space should be related to higher levels of well-being are not clearly understood. In a recent discussion paper, de Vries and Snep, (2019) highlight that the concept of biodiversity stems from the discipline of ecology, where diversity is seen as a function of an ecosystem. A place with high biodiversity may not be a place that invokes higher levels of subjective well-being, because it may be considered too wild, or contain dangerous species, and therefore discourages use or exposure. To some extent, this idea is supported by the negative associations we found with the new Wild habitat category. The interconnected relationships between habitat types, biodiversity of particular taxonomic groups and well-being are not understood. It might be that for individuals to perceive and be exposed to birds and butterflies, and therefore achieve any associated well-being benefits, the habitat in which they experience this has to enable access and use, which might not necessarily be those places with higher levels of habitat diversity. Also, we do not find any association between plant diversity and well-being. Surprisingly, we do not find correlation between any species richness measure and any habitat diversity measure, which is a contrasting finding to other studies who find a correlation between bird species richness and both plant species richness and habitat diversity (Bino *et al.* 2008).

5.5.4 Are there any associations between metrics of habitat, habitat diversity and biodiversity?

It is likely that the context of a site matters. The wider context of a site is likely to influence the biodiversity inside it, for example adjacent road networks (Villaseñor & Escobar 2019). Moreover, an urban park with a big expanse of amenity grassland, and therefore potentially low levels of habitat diversity, provides more opportunities for individuals to sit and observe butterflies and birds. Conversely, a sports playing field with similar habitats and levels of biodiversity has a primary use for team sports, and therefore is less likely for individuals to notice butterflies and birds present.

To examine this, we compared the levels of habitat diversity and biodiversity across the Planning Policy Guidance 17 (PPG17) land use categories. Table 5.8 (and Figures S5.8-17 in the appendix) show that the highest mean levels of biodiversity are found for Natural and semi-natural urban greenspaces, and the highest mean levels of habitat diversity in the categories Cemeteries and Churchyards and Parks and Gardens. However, what is evident from the boxplots is that the spread of biodiversity scores within each land use category are highly positively skewed, with many larger outliers. This suggests that although average habitat and biodiversity levels may generally differ across land uses, there is more variety within types than across types. Therefore, this supports the suggestion that the context of each individual LSOA or OSS needs to be accounted for when examining the relationship between habitat and biodiversity features of a site and well-being.

We find some evidence of a relationship between NDVI (mean and standard deviation) and subjective well-being. NDVI metrics are commonly used metrics in the literature to examine the relationship between the natural environment and well-being and positive associations have been found in several studies (Crouse *et al.* 2017; Mavoa *et al.* 2019a; Pereira *et al.* 2013; Reid *et al.* 2018). NDVI is a measure of vegetation productivity or health even, but can be used to distinguish between vegetated and non-vegetated surfaces. Therefore, our positive findings suggest that LSOAs with higher levels of vegetation cover and more productive vegetation, as well as more variability in this productivity and land use, are associated with higher levels of self-reported general health. This may be due to increased opportunities for outdoor physical activity, or other health-related phenomena such as a diverse body microbiome (Pearson *et al.* 2020).

Studies have suggested that NDVI, especially the standard deviation, is a suitable proxy for biodiversity (Gould 2000; Mavoa *et al.* 2019a; Pearson *et al.* 2020), and that mean NDVI represents a consistent and therefore spatially comparable metric of greenness. However, we find little correlation between our NDVI metrics and the habitat and biodiversity metrics used in this study (Table 7). This lack of correlation indicates that in this study NDVI mean and standard deviation in OSSs are not suitable proxies for habitat diversity or plant species richness, and that it should be used alongside other vegetation metrics. These findings are similar to those found by Taylor et al., (2018), who found no significant relationship between mean NDVI and bird species richness in Auckland, New Zealand (although they found positive associations in Wellington, Sydney and Melbourne). Other studies have found NDVI (mean and variation) highly correlated with species richness in urban environments. For example, Bino et al., (2008) found mean NDVI highly correlated with both plant and bird species richness in Jerusalem, Israel. Interestingly, they found a linear relationship with plant species richness but a hump-shaped relationship with bird species richness when studied at varying spatial scales. This hump-shaped relationship at small or localised scales has been found in other studies who vary spatial scale, concluding that the shape of the relationship between productivity and biodiversity varies with geographical scale, taxonomic group and ecosystem (Seto *et al.* 2004). It has also been found to vary across different diversity dimensions (Brun *et al.* 2019), and with particular spatial relationships between species and habitat (Bonthoux *et al.* 2017).

5.5.5 Do different methods for capturing exposure yield different results?

In this study we use two different methods to capture exposure to green- and bluespaces, neighbourhood (LSOA) composition, and distance-decay functions to OSSs. The former benefits from being a well-recognised and standardised administrative unit, allowing for integration with key explanatory variables and a relatively consistent unit for comparison. However, its somewhat arbitrary boundary might not best reflect how an individual uses their surroundings. The distance-decay method attempts to address this shortcoming by removing all need for arbitrary boundaries and distances, and accounts for the effect of every OSS in Greater London, weighting the effect by distance from the individual's residential location. We find many different results between the two methods, perhaps partially because the LSOA method captures all habitats and biodiversity within the boundary, whether it's inside an OSS or not, whereas the distance-decay method is based on measures inside OSSs only. Therefore habitat, biodiversity and greenness occurring in other potentially important land uses, such as streetscapes and domestic gardens for example, are not accounted for in the distance-decay method.

This is important because attempting to understand how biodiversity relates to human well-being requires the consideration of how exposure if measured. In this study, we explored the effects of biodiversity in relationship to residential location, assuming this is the place in which an individual is exposed to biodiversity. The distance-decay method allows us to expand this from the neighbourhood to the whole city. However, using this method we only measure the biodiversity of OSSs. The location of biodiversity, i.e. the context of it, is likely to be important. Green- and bluespaces in urban environments are by definition influenced, designed and maintained by humans, for certain functions.

The differences found between the two surveys (and to some extent the exposure methods too) suggest that there are important differences between the surveys in how individual well-being is related to aspects of the natural environment. Indeed, this supports previous research that found a significant positive relationship between urban greenspace and well-being using the BHPS in England (White *et al.* 2013b), but found no relationship with the UKHLS (Houlden *et al.* 2017). Respondent attrition is a common problem in panel surveys, and Lynn and Borkowska, (2018) found attrition rates in both the BHPS and UKHLS were greater amongst younger age groups, men, black people and participants on lower incomes. Moreover, they find the UKHLS main sample had a higher attrition rate than the BHPS. This might be important; several studies have highlighted the potential significance that individual characteristics play in the relationship between well-being and the natural environment. For example, the relationship between residential greenspace and mental distress was found to vary with age and gender in nine waves of the BHPS (Astell-Burt *et al.* 2014c). In another study, only those individuals in the lower socio-economic status category, as measured by education attainment, were found to have a significant association between well-being and surrounding greenspace (de Vries *et al.* 2003). Additionally, the >120minute physical activity threshold for achieving well-being benefits from neighbourhood greenspace was significant for the White British category but not for others, suggesting potential differences by ethnicity in relationships between natural spaces and health and well-being benefits in England (White *et al.* 2019). If those in younger age groups, men, black individuals and those with lower incomes are under-represented in both surveys, and more so in the UKHLS, it seems likely that this will contribute to different outcomes in the analyses.

5.5.6 Implications, limitations, and future work

Limitations and future research

There are several problems with using specific species, taxonomic groups or habitat diversity as a measure of biodiversity in well-being studies. Biodiversity monitoring data have many known issues relating to biases in data collection e.g. observer bias, taxonomic bias (Isaac & Pocock 2015; Troudet *et al.* 2017). Despite our biodiversity database containing large numbers of records across an entire city scale, survey effort is notably higher in sites that are open to the public and at places of higher accessibility e.g. large parks such as Richmond Park, and along paths and roads. Many sites do not have any biodiversity records in the dataset, which implies a lack of survey effort rather than actual recorded absences of species. All three categories (butterflies, birds, and plants) show positive skew, with many spatial units containing very low numbers, and with a handful of sites containing much larger numbers of records and species. Number of species recorded has been previously shown to be positively correlated with survey effort. Some sites may have paid employees who conduct surveys, or active public/community groups who make recordings. Indeed, research suggests that survey effort increases in areas of higher affluence, as residents will tend to have more free time and greater interest in environmental issues.

Higher levels of survey effort may also be indicative of places of known higher levels of biodiversity or presence of interesting, charismatic, or rare species. Survey and citizen science data tends to be skewed towards slower, brighter, bigger species, as they are easier to identify and therefore disproportionately sighted in comparison to those that are smaller, quieter, more rare, and less aesthetically pleasing. Arguably, these will be the species that are better perceived by people, so more likely to influence their well-being, if we assume that this is the pathway to influencing well-being. Citizen science data also suffers from only capturing presence data, not absence data, and survey effort tends to be focussed on weekends and in better weather. However, it could be argued that these issues affect all biodiversity data, and that our dataset is not so different from others.

In this study, we removed all species records with a date preceding 1990, to match the data collection timeframe of our population sample data that started in the BHPS. However, we then also applied this data to the UKHLS waves, the latest of which was taken in 2018. This might represent some error in our estimates. However, producing time series biodiversity estimates for each year from the database would likely introduce further error, as survey effort was not consistent through time. Many observations might be opportunistic rather than systematic.

We have attempted to correct for differences in survey effort by aggregating all observations through time for a location together, effectively allowing temporal survey effort to contribute to the total richness score. While this has some obvious issues, such as not accounting for changes in species composition over time, it does provide slightly more robust estimates of biodiversity across space. Other methods for accounting for survey effort might include using interpolated data layers from point observations, such as species atlas data like that used by Wheeler et al., (2015). However, this type of data is often much less spatially resolved, so will undoubtedly introduce measurement error in exposure estimates.

It is likely that the relationship between well-being and biodiversity is not linear. For example, previous research showed that people have a preference for intermediate levels of plant diversity (Lindemann-Matthies & Matthies 2018). It could be that places with high biodiversity are considered too wild, or that they contain species that are dangerous, and therefore are considered dangerous and unsafe to visit (de Vries & Snep 2019). It is also likely that not all species contribute equally to how an individual perceives biodiversity. Common bird species for example, such as pigeons, may not contribute equally to a more rare, colourful or tuneful species (Cameron *et al.* 2020). Conversely, certain rare butterfly species are also small and difficult to detect, so therefore rarity is not necessarily an important factor. Additionally, certain species that are invasive and represent a potential threat have been shown to have a negative association with well-being (Jones 2017). Some evidence suggests that abundance may be more important than richness (Cracknell *et al.* 2017). Given that abundance in urban areas is decreasing for many species, but at differing rates dependent on functional traits such as mobility (Dennis *et al.* 2017), this is particularly important to capture temporally. Therefore, future research could observe different standard measures of biodiversity such as abundance, as well as observing functional or phenotypical traits rather than simple richness, as this may be more useful as they are more easily perceived by individuals, such as plant height or colour of fish (Botzat *et al.* 2016; Sandifer *et al.* 2015; Williams *et al.* 2015).

A common assumption here, and in many similar studies, is that local natural environment conditions aggregated up to larger unit statistics (e.g. LSOAs and OSSs) are reasonable proxies for the entire unit. LSOAs and OSSs are heterogeneous in terms of the natural environment composition. By using large, detailed databases containing the locations of biodiversity sightings, we are able to provide relatively accurate representations of how biodiversity varies across space. However, despite the database being quality checked and flagged by experts, the spatial accuracy of the georeferences varied across surveys. The majority of records contained easting and northing coordinates with high spatial reliability. However, some records were less reliable, with coordinates reflecting an approximate location, or indeed the centroid of a site. If that site was large, this introduced error into how that record was aggregated into the spatial units in our analysis. This is particularly true for the LSOA-level analysis. Perhaps this is more of a concern for less-mobile species and plants. Similarly, the habitat data contained percentage cover of polygons but did not indicate where in that polygon the habitat occurred. This became problematic when aggregating habitat statistics up to OSS and LSOA level, particularly where polygons intersected. These issues of ecological fallacy are common in such studies and require the assumption that aggregated statistics reasonably represent actual exposure. The same applies when estimating the relative exposure by local resident populations (Wheeler *et al.* 2015). LSOAs are likely to be heterogeneous in terms of the natural environment composition, and any estimations of exposure at the individual-level from aggregated statistics also suffer from ecological fallacy issues and aggregation bias.

Ultimately, all exposure methods and geographical scales are subject to spatial error in the estimation of exposure to the natural environment. Whenever statistics are calculated using aggregated spatial data, the issues associated with the Modifiable Areal Unit Problem (MAUP) will also affect the estimate (Dark & Bram 2007). For example, if an OSS was long and thin, how an individual is exposed to a particular habitat is very dependent on their residential location, as opposed to that of a more uniform, circular OSS. This has implications for how exposure to the natural environment is best captured and quantified. For example, the size, shape and aggregation level used when neighbourhoods are the exposure unit, and the distance used when using buffer zones, will give different exposure statistics. This issue of OSS shape and how to apply biodiversity and habitat metrics to it became clearly apparent when we considered the River Thames as an example. The River Thames OSS polygon is long, thin and spans the entire width of Greater London. When aggregating biodiversity metrics to the entire polygon, numbers no longer necessarily reflect the biodiversity that individuals will be exposed at different points along the river.

Similarly, the dataset used to represent the natural environment will also introduce error into the estimate. For example, the size and shape of green- and bluespaces, or the NDVI products of differing spatial resolutions. Interestingly, we find that our NDVI standard deviation metrics for OSSs in 2000 and 2018 are not significantly correlated (Table 7). They are based on two different products, Landsat 7 and Sentinel 2 respectively, and were used to best reflect the different time periods of the two population samples. The former has a resolution of 30 m and the latter of 10 m. It is likely that this difference in resolution means that there is error captured in the variation in values within a spatial unit (LSOA or OSS). This has been highlighted in previous studies (Reid *et al.* 2018; Su *et al.* 2019) and therefore caution must be taken when considering the spatial resolution and scale in measurements of exposure to the natural environment.

We noticed that despite attempting to remove water bodies from the NDVI analysis by removing all pixels with a value of 0 or below, several water bodies still remained in the resulting layer. Presumably this was due to overhanging vegetation on the edges of water bodies, or overlapping NDVI pixels with polygon edges. An alternative method would be to identify polygons relating to water bodies and remove them by this attribute.

In this study we have examined LSOA and OSS biodiversity. We have not been able to ask questions about the distribution of biodiversity in these locations. For example, we cannot say if proximity to one highly biodiverse OSS is more important for well-being than proximity to several averagely-diverse OSSs. A good next step here would be to disentangle neighbourhood sources or hotspots of biodiversity and measure the biodiversity in the network of green infrastructure. We also have not considered whether accessibility (private, public, fee-paying etc) of the open space sites influences the relationship between biodiversity and well-being, assuming that well-being gains/losses are only achieved when individuals access green- and bluespaces (Biernacka & Kronenberg 2018). Also, the distance-decay method uses Euclidean distance to the nearest edge of all OSSs. While this is an improvement on other methods, such as to the site centroid, Euclidean distances are not accurate representations of actual travel times. Introducing network analysis methods, which use known travel routes such as roads and footpaths, would likely give more accurate distance values.

We cannot be sure if our findings found here for London will apply more broadly to other large urban areas similar to London, such as other English cities and that across the Global North. For example, previous studies find contradictory relationships in Sheffield, UK (Cameron *et al.* 2020). Despite Londoners enjoying greater access to public greenspace than the national average; 44% of Londoners living within a five-minute walk of a park, compared to 28% of people across Britain (Office for National Statistics 2020b), Londoners have just 18.96 m^2 of provision per person, which is almost half the national average (Fields in Trust 2020). This potentially makes the relationship between well-being and open space in London relatively unique in the country. Other studies suggest clear national-level differences in how biodiversity is distributed across cities (Bino *et al.* 2008; Tryjanowski *et al.* 2017), which is likely explained by many complex and interrelated issues, such as national urban design and planning, population characteristics, land cover and use, species compositions and environmental gradients. For example, our study is based in a large city in England, arguably a relatively low biodiverse location when compared to other parts of the world. It is recognised that much research that observes well-being impacts of the natural environment is conducted in the Global North, and therefore there is a definite bias in our understanding. Perhaps in relatively low biodiverse places, individuals are less sensitive to changes in biodiversity than those where high levels of biodiversity are the norm. A comparative study in other parts of the world would be an important way to examine the effect of this. This would also bring to light any cultural differences in how human well-being is related to biodiversity.

Several studies have highlighted the potential significance that individual characteristics play in the relationship between well-being and the natural environment. For example, gender (Annerstedt *et al.* 2012), socio-economic status and protected characteristics such as BAME status and disabilities (Boyd *et al.* 2018). Additionally, there is some evidence to show that individuals' preferences, beliefs and perceptions about nature and biodiversity are important to consider too, such as nature connectedness and perceived biodiversity (Pett *et al.* 2016; Schebella *et al.* 2019). A different approach to this work could explore for any differential relationships based on individual characteristics through mediation and moderation analyses. This might help to account for the demographic differences reported between the two population samples.

The most important determinant of our confidence that the effect estimate is causal is whether the change in exposure to habitats and biodiversity is plausibly unconfounded (Strumpf *et al.* 2017). I include a suite of explanatory variables in my model specifications to control for heterogeneity in the model. The use of key individual- and neighbourhood-level control variables captures important differences in the economic, social and environmental conditions that are likely to affect both subjective well-being and the natural environment. Fixed effects controls for any time-invariant omitted variable bias in the model specifications. However, to be able to confidently assert a causal relationship, we have to be sure that any changes in exposure within an individual are effectively random. Unaccounted time-varying factors and reverse causality may still bias our models. For example, it might be that individuals with higher levels of subjective well-being choose to move to places that are greener and therefore more biodiverse, or that those who feel more connected to nature, and therefore potentially more affected by nature, chose to live in locations where they are more exposed to biodiversity. Those individuals who are wealthier or have a higher socio-economic status are more likely to move to places with higher levels of biodiversity for example, known as The Luxury Effect (Leong *et al.* 2018). While we attempt to control for some of these factors, using household income and deprivation metrics as control variables, and fixed effects controls for individual-level factors that do not change through time, it is likely that there are other sources of heterogeneity in the models that bias our estimates and also lead to low R^2 values. Future work could attempt to account, and control, for this spatial variation in the relationship between well-being and habitat and biodiversity by using spatial regression models, such as Geographically Weighted Regression. These allow model parameters to change across space, therefore accounting for any clustering effects (Houlden *et al.* 2019b).

Implications and conclusions

In the UK, there is growing recognition in government that green- and bluespaces are critical assets for delivering health and well-being benefits to individuals (Public Health England 2020). However, public sector expenditure on biodiversity in the UK, as a proportion of GDP, has fallen by 42%, following a peak in 2008/9 (State of Nature Partnership 2019). There is a clear need from both policy and conservation organisations to better understand the link between biodiversity and human health and well-being (Lovell *et al.* 2014), in order to better promote both.

This study finds several important relationships between habitat types and subjective well-being in London, with some evidence of a relationship between well-being and biodiversity, and no evidence with habitat diversity. We present the use of openly available habitat and biodiversity monitoring data for such studies, and identify some key issues and considerations when doing this. We also find that our results are dependent on the exposure method, population sample and well-being measure used. This highlights the need for future research to identify how the relationship between well-being and habitats and biodiversity varies across different demographic and socio-economic groups, across different spatial scales of exposure, and the mechanisms that underpin them.

Chapter 6: General discussion

6.1 Summary of thesis findings

In this thesis, I have used large, longitudinal panel data to attempt to capture and quantify the effect of the natural environment on subjective well-being. Specifically, I have examined the impact of air pollution, land use and habitat type, site designation, and biodiversity of neighbourhoods and open spaces, on up to three measures of subjective well-being for adults in England and then London. I used two panel surveys to conduct these analyses, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), both part of the Understanding Society project.

In chapter 2, I estimated the well-being effect of nitrogen dioxide (NO_2) on life satisfaction. I used annual ambient outdoor NO_2 measurements to calculate air pollution levels for each lower super output area (LSOA) in England for each year, and then estimated the effect on self-reported life satisfaction, captured in the BHPS and UKHLS. I found a significant and negative relationship between neighbourhood NO_2 levels and life satisfaction, before and after adjusting for a suite of explanatory variables. The results suggest a 10 $\mu g/m^3$ increase in LSOA annual average NO_2 levels are associated with a 0.03 decrease in life satisfaction (on a 1-7 Likert scale). Using standardised coefficients, I find the estimated disutility effect from an average annual ambient level of 40 $\mu g/m^3$ which is the legal EU limit (and exceeded in many parts of the UK) would be comparable to that of many big-hitting life events such as unemployment, marital separation and widowhood.

In chapter 3, I used the Planning Policy Guidance Note 17 (PPG17): *Planning for open space, sports and recreation*, a formal open space typology used across the UK for land use planning guidance, to categorise open spaces in Greater London, UK, and examine the effect of LSOA land use types on subjective well-being. I use three measures of subjective well-being from the BHPS and the UKHLS in this chapter to explore the multi-dimensional nature of well-being using life satisfaction, mental distress (GHQ) and self-reported general health. I find several open space categories have positive, and also several to have negative, relationships with subjective well-being. Golf courses, Allotments, Playing fields and Equestrian centres had the largest positive median effect sizes, whilst surprisingly Village greens, Country parks, Amenity green space and Nature reserves had the largest negative median effect sizes. I also found that all three blue space categories were associated with higher levels of well-being. I found the PPG17 typology problematic when assessing the well-being benefits of open spaces, due to the broad nature of the higher categories. When aggregating the land use types into a new typology, of greenspace, bluespace, and green- and bluespace combined, I find that only the bluespace category is related to higher levels of well-being.

In chapter 4, I examined the association between ecological quality of public natural spaces (specifically its importance for nature conservation) and subjective well-being in London. In this chapter, I also explored the impact of private open spaces on well-being, and if this affects the relationship between public open spaces and well-being. I use the Areas of Deficiency to Sites of Importance for Nature Conservation (AoDs to SINCs) calculated by GiGL, calculated using network analysis along known walking routes, to identify areas that are outside a 1km walk from a known SINC access point. I use two measures of well-being from the BHPS and the UKHLS: life satisfaction and mental distress (GHQ) and each individual's residential postcode identifier to assign the location as inside or outside an AoD to SINCs. The results suggest that living within a 1km walk of a SINC is associated with higher levels of life satisfaction, but no relationship is found with mental distress. The analysis is repeated using all public open spaces (POS), using the Areas of Deficiency to POS, and there are no significant relationships with either well-being measures, or any of the categories of POS. Therefore, the findings suggest the *quality* of public green and blue spaces in London is important for the well-being of residents in London. I included access to private open space and found a positive, significant and direct relationship with both measures of well-being, which is separate to that with public open space. Therefore both public and private green and blue spaces are important for well-being for residents in London. I also conducted the analysis using a coarser residential address identifier, to explore the effect of spatial resolution on the estimates. I used LSOA population-weighted centroids as an alternative to postcode unit centroids, and found no relationships between well-being and proximity to SINCs. This is an important finding, and suggests that estimation error introduced by using inaccurate residential location data may lead to inaccurate measurements of exposure to the natural environment.

In chapter 5, I examined the relationship between habitat and biodiversity and subjective well-being. I used detailed habitat, species presence databases and Normalised Difference Vegetation Index (NDVI) layers for Greater London to calculate environment metrics of two different spatial units: LSOAs and open space sites (OSSs). In the LSOA analysis I calculated habitat and biodiversity scores for each LSOA in Greater London and then applied these scores to each individual in the population sample, based on their residential LSOA. For the

OSS analysis, I calculated habitat and biodiversity scores for each OSS in Greater London, then constructed distance-decay functions to calculate exposure scores for each individual based on their residential location (six-digit postcode-centroid). I then applied these exposure scores to the population samples and conducted fixed effects regression analysis. I used three measures of subjective well-being from the BHPS and the UKHLS in this chapter to explore the multi-dimensional nature of well-being using life satisfaction, mental distress (GHQ) and self-reported general health. I found several positive and negative associations between habitat types and subjective well-being in both the LSOA and distance-decay analyses. For example, I found the strongest evidence for a positive association with Allotments, Herb-rich grassland and Still water, and that for negative associations with several woodland types (Native and Non-native broadleaf woodland) and several semi-wet and wild types (e.g. Swamp, Intertidal and Saltmarsh). I found some association between biodiversity and subjective well-being, and no association with habitat diversity. These findings suggest the importance of habitat types for well-being, and the mixed biodiversity results suggest potential relationships with butterfly and bird species richness. However, much more research is needed to be able to draw more robust conclusions regarding biodiversity and well-being.

There is increasingly compelling evidence that suggests exposure to the natural environment is associated with a huge range of health and well-being benefits (Sandifer *et al.* 2015). However, this body of literature hugely varies across studies in how both well-being and the natural environment are defined and measured, how exposure is operationalised, the spatial scales used, the sample populations studied, the effect sizes found in the relationship, and to what extent the findings are causal (Houlden *et al.* 2018; Labib *et al.* 2020b; Marselle *et al.* 2019). These differences make this body of work fascinating and insightful, but they also expose research gaps in our understanding. In this thesis, I have attempted to address some of these gaps by differentiating between different types and characteristics of the natural environment, and identifying which are important for well-being and to what extent. I have used several approaches to model exposure to the natural environment, using different measures of neighbourhood and distance. I have used two different population samples from two large panel surveys, using up to three different measures of subjective well-being. I employed fixed effects regression to allow the use of longitudinal well-being data, as a potential improvement on cross-sectional analysis, and include a range of important covariates to control for potential biases in the estimates.

The main aims of this thesis were (1) to identify which characteristics and qualities of the natural environment are important for subjective well-being, (2) to examine if the *quality* of the natural environment affects subjective well-being, and if so, to estimate the effect size, (3) to consider different ways of measuring proximity or exposure to the natural environment. For the remainder of this chapter I will discuss the key findings in light of these aims. I will also discuss the implications of these findings, highlight the limitations to the approaches used and identify some key suggestions for future research.

6.2 Aim 1: To identify which characteristics and qualities of the natural environment are important for subjective well-being

6.2.1 Overall green- and bluespace

Much work that examines the relationship between well-being and the natural environment looks at the amount or proportion of green- and bluespace in an individual's residential surroundings (de Vries *et al.* 2003; Mitchell & Popham 2008; van den Berg *et al.* 2015; Wheeler *et al.* 2015). Many studies conclude that individuals living in greener places have higher levels of well-being. The same has been found for individuals living with higher levels of bluespace in their surroundings (de Vries *et al.* 2016; Nutsford *et al.* 2016; Pasanen *et al.* 2019). However, there are also studies that find no relationship. In this thesis, I find mixed results between subjective well-being and overall residential green- and bluespace. When using overall proportion of green- and bluespaces an individual's LSOA (as measured using the Generalised Land Use Database (GLUD) or all Open Space Sites (OSSs)), I do not find any significant associations with any measures of subjective well-being. These negative findings are important, because they support other studies that also do not find any relationship with this categorisation of natural spaces (Rugel *et al.* 2019; Triguero-Mas *et al.* 2015; White *et al.* 2017).

In chapter 5, I use NDVI as a measure of "greenness", as an alternative to land use classification in the OSSs and GLUD datasets. Using the mean NDVI score within an individual's LSOA, I find a significant and positive relationship with self-reported general health, using the UKHLS sample. This finding supports other studies that also find a relationship between NDVI "greenness" and well-being (Dzhambov *et al.* 2018; Gascon *et al.* 2018). However, I do not find a relationship when using the BHPS sample, and I also do not find a relationship with life satisfaction or mental health (as measured by the GHQ). I also do not find a relationship when using a different method to measure exposure (distance-decay analysis) to NDVI in OSSs.

Overall, these findings suggest limited associations between aggregated categorisations of green- and bluespaces and well-being. One explanation for this could be because such generalised datasets do not allow the distinction between different types of land use, as well as differential quality of these places. This supports the findings of several studies who call for more research into identifying the characteristics and qualities of green- and bluespaces that relate to well-being (Akpinar *et al.* 2016; Nieuwenhuijsen *et al.* 2017; van den Berg *et al.* 2015). Additionally, these findings also suggest that different measurements of natural places, i.e. land use datasets (OSS) vs remotely sensed metrics such as GLUD and NDVI datasets, will produce differing relationships with well-being. This could be because the remotely sensed products are measuring slightly different aspects of the natural environment. For example, NDVI measures photosynthetic health of vegetation or "greenness", whereas the OSS dataset defines places by land use. NDVI does not capture bluespace, which is has been shown to be important for well-being. Both NDVI and GLUD identify domestic greenspace, which most land use datasets exclude, and as shown in this thesis, are important for well-being.

6.2.2 Type of green- and bluespace

There have been recent calls for more research to identify the 'attributes' and 'types' of green- and bluespace that are associated with specific health benefits (Akpinar *et al.* 2016; Hartig *et al.* 2014; Wheeler *et al.* 2015). This need is also highlighted in our findings in the previous section. In this thesis, I disaggregated open spaces in London in a number of ways: differentiating between green- and bluespace, using a land use typology the Planning Policy Guidance 17 (PPG17), examining the effect of private or domestic open spaces compared to public open spaces, and by categorising different habitat types.

6.2.2.1 Bluespace

A key finding in this thesis is that bluespaces are important for subjective well-being. In chapters 3 and 5, I found significant positive relationships between well-being and aggregated bluespace (or water) categories. These findings suggest that bluespaces provide unique well-being benefits that are different to those found with greenspaces. This distinction between green- and bluespaces is important, and adds to the current literature that explores the differential positive effect of proximity to blue environments on human well-being (Finlay *et al.* 2015; Mavoa *et al.* 2019a; Nutsford *et al.* 2016; Triguero-Mas *et al.* 2015; White *et al.* 2013a).

It is also important here to distinguish between the different types of bluespace. There were three specific 'blue' open space subcategories in the OSS dataset: Canals, Rivers and Reservoirs, and these were all significantly and positively associated with two measures of well-being across both surveys (BHPS and UKHLS). In chapter 5, using Phase 1 habitat types, the category Still water is positively associated with well-being, although the River category is not. Therefore, just like it is important to distinguish between different types of greenspaces, it is important to differentiate bluespaces too. Additionally, each bluespace type is associated with a different combination of well-being measures. This suggests that different types of bluespace are associated with different well-being pathways, and that there are different mechanisms here for achieving well-being benefits. For example, they may differentially offer opportunities for physical activity, different aesthetical values, or, specific to London or any large city, associated facilities e.g. South Bank promenade.

6.2.2.2 Land use

In chapter 3, our findings suggested that open spaces associated with recreational or physical activities and those involving a sense of community amongst users, are positively associated with subjective well-being. In terms of median effect sizes, the PPG17 subcategories with the greatest well-being benefits were Golf courses, Playing fields, Equestrian centres, Allotments and Other. These findings are consistent with current literature that suggests green and blue open spaces provide well-being benefits by providing opportunities for physical activity, by building social cohesion, and positive feelings of purpose (Nieuwenhuijsen *et al.* 2017; van den Berg *et al.* 2010b). However, it is likely that many of these sites have restricted or private, or semi-private (e.g. fee-paying) access only. Whether the well-being benefits associated with living near to these land uses are achieved by residents directly accessing and using these sites, likely with allotments, or by some other means, we cannot say. For example, golf and horse-riding are relatively specialist interests and do not appeal to the broader community, and playing fields are likely to be used by sports clubs or schools. Certainly, evidence suggests that neighbourhoods with large green and blue open spaces are related to increased house prices, lower population density, or by improving the broader natural environment i.e. cleaner air or higher biodiversity (Czembrowski & Kronenberg 2016; Laffan 2018). It therefore becomes important here to consider causality of the relationship. For example, it could be that golf courses inflate local house prices, and therefore individuals that live near them are on average wealthier. Given that wealthier individuals, or those with a higher socioeconomic status, are more likely to report higher levels of subjective well-being, the relationship between proximity to golf courses and well-being is due indirectly to selective residential sorting.

I also found negative associations with several land use categories, many of which are surprising given our current understanding from previous literature. For example, the results suggest a negative relationship between well-being and Nature reserves, Amenity greenspace, Village greens and Country parks. These are sites that are likely to be maintained and managed for recreation and social purposes, and in some instances, for higher levels of biodiversity and cleanliness. This contradicts previous research that suggests cleaner and/or more biodiverse locations are associated with higher levels of well-being (Brindley *et al.* 2019; Wheeler *et al.* 2015). As above, the context of these sites might be important here, particularly in London. Many of London's newest nature reserves are built on abandoned industrial land, such as Gillespie Park and Railway Fields (Fields in Trust 2019), this may mean the surrounding area is perceived as relatively undesirable, or surrounded by a residential community with lower socioeconomic status and therefore relatively more likely to report lower levels of well-being. Other surprising outcomes in this chapter are that I find no significant relationships between well-being and woodland categories and Parks and gardens. It could be that certain open spaces may be considered or perceived as unsafe, such as large amenity spaces or urban woodlands (Milligan & Bingley 2007b). To an extent, we attempt to control for these factors by using the crime domain of the Indices of Multiple Deprivation but as this analysis was at the LSOA-level, it may mask some of the more localised components of this relationship.

6.2.2.3 Habitat types

Several findings from chapter 5 also support these findings. In chapter 5, I examined habitat types within LSOAs and OSSs and explored their relationships with subjective well-being. In this chapter, I found evidence of a positive relationship with Allotments, and also negative relationships with woodland categories, both supporting the findings from the land use analysis in chapter 3. Interestingly, I do not find any associations between any measure of well-being and Amenity grassland, which is the likely predominant habitat type in several of the land use categories, such as Amenity greenspace, Village green, and Playing fields. This might suggest that habitat types in these land use categories are not the characteristics of these OSSs that are important for the well-being relationships found.

I found evidence of positive associations between species-rich grasslands, such as Herb-rich grassland, and well-being. One explanation for this may be due to the relatively higher levels of biodiversity when compared to other types of grassland (see the biodiversity section below for further discussion). In the distance-decay analysis I find negative associations with semi-wet types (e.g. swamp) and wild or changeable (e.g. saltmarsh) habitat types. The distance-decay results vary quite significantly from the LSOA-level results (discussed later in this chapter) so this may be an artefact of the exposure method used. However, this may also be explained by these types of habitats being perceived as unpredictable and unsafe by users.

Overall, the use of land use categories and habitat types to characterise open spaces in London is a methodological improvement on using aggregated greenspace datasets. It has allowed different questions to be addressed and provides useful insight into how different aspects of green- and bluespaces are related to well-being.

6.2.2.4 Private open space

Common definitions of urban greenspaces include public open spaces, such as parks, woodlands, children's playgrounds and community gardens, and semi-public spaces such as allotments, golf courses, sports fields and wildlife reserves (Taylor & Hochuli 2017). These categories are all included in the PPG17 land use typology used in chapter 3. However, these public and semi-public spaces are part of a larger matrix of green infrastructure in an urban area. Other types of urban greenspaces may include private spaces, such as domestic gardens, and these are likely to also contribute to the subjective well-being of residents. However, these other types of greenspace are often excluded from studies that look at the relationship with well-being.

In chapter 4, I examined the relationship between well-being and private, or domestic, open spaces, and explored if having access to a private open space impacted the relationship between well-being and proximity to public open spaces. I found that access to a garden or terrace was associated with higher levels of both life satisfaction and lower levels of mental distress. These results suggest the importance of private open space for individual well-being, supporting previous research in this field (de Bell *et al.* 2020b; de Vries *et al.* 2003; Dennis & James 2017; Mavoa *et al.* 2019a). Our results in chapter 4 also suggest that access to private open space has a direct association with life satisfaction, and that this association is separate to that found with public open spaces. In other words, both private and public open spaces are associated with higher levels of life satisfaction.

My findings support previous research that suggests well-being benefits may be achieved by allowing individuals a different type of experience with the outdoors to public spaces. Gardens are private spaces and therefore may provide opportunities to experience and interact with nature and outdoor activities in a manner that suits the individual. Activities such as gardening and bird watching for example have been linked to improved well-being (Cox & Gaston 2016). Benefits from private gardens could be achieved passively and therefore do not require visits or time spent within them (Coldwell & Evans 2018). There is a large body of evidence to show that private green spaces act as therapeutic landscapes (van den Berg *et al.* 2010b) and that green views from buildings provide restorative benefits to individuals (Kaplan 2001). Private spaces may also be associated with feelings of security and ownership (de Bell *et al.* 2020b). Another explanation for the relationship between access to private open space and life satisfaction maybe explained through other factors unaccounted for in our analysis. Properties with access to domestic space tend to be in neighbourhoods that are considered more desirable, although we try to account for this by including an individual's neighbourhood satisfaction and deprivation indices for each LSOA.

Overall, in this thesis I have shown that green- and bluespaces are heterogeneous, and that different characteristics and types of open space are important for individual well-being. Using disaggregated datasets has allowed me to explore which characteristics are important for well-being, and what the direction and effect size is.

6.3 Aim 2: To examine if the *quality* of the natural environment affects subjective well-being, and if so, to estimate the effect size

Recently, there has been an increased interest in examining how the *quality* of the natural environment is related to well-being (Francis *et al.* 2012; Garrett *et al.* 2019b). The quality of urban natural environments has primarily been defined either by factors pertaining to its attractiveness, aesthetics and naturalness, or to factors relating to its use, such as cleanliness (Brindley *et al.* 2019), safety, maintenance and amenity features present (Wood *et al.* 2018). Other studies have begun to explore metrics relating to the ecological quality of the natural environment, such as biodiversity and protected status (Cameron *et al.* 2020; Wyles *et al.* 2019). However, this body of research is small and our understanding of the relationship, its direction, size and underlying mechanisms, are all currently underdeveloped (Marselle *et al.* 2019).

In this thesis, I examine two measures of *quality* of the natural environment: air pollution (NO_2) and biodiversity (measured by several proxies: site designation, species richness, habitat diversity and the NDVI standard deviation). Across these studies, I find differing results, depending on the metric of quality used. I find a negative relationship between NO_2 and life satisfaction in England. In London, I find that living within a 1km walk of a SINC is associated with higher levels of life satisfaction (and that there is no relationship found between all public open spaces). I also find some evidence that neighbourhood-level butterfly and bird species richness, and NDVI standard deviation are all associated with self-reported general health, but that there is no relationship with neighbourhood habitat diversity. These findings contribute to a small but growing body of literature which finds mixed results when exploring the quality of the natural environment.

6.3.1 Air pollution

In chapter 2, I find a 10 $\mu g/m^3$ increase in annual average NO_2 levels in one's LSOA is associated with a 0.03 decrease in life satisfaction (on a 1-7 Likert scale). This finding supports much of the epidemiological literature which suggests that exposure to NO_2 can have a substantive detrimental effect on health (Brook *et al.* 2010; Brunekreef *et al.* 2015; Shah *et al.* 2015) which will of course in turn affect individuals' subjective well-being. This result also contributes to the growing body of work that finds NO_2 has a negative effect on self-reported measures of well-being (Du *et al.* 2018; Mackerron & Mourato 2008; Welsch 2002, 2007).

Due to the importance of NO_2 found here, this variable was included in each subsequent analysis as a control variable. However, we did not find any significant relationships between NO_2 and well-being in these regression models. This could be because subsequent chapters were conducted for London only, and that the relationship is different at this geographical scale. Recent work also does not find a significant relationship, for example Krekel and MacKerron (2020) find no clear relationship between air pollution and momentary happiness in London. It could be that individuals living in London are less affected by NO_2, in terms of subjective well-being, than those outside of the city, despite London experiencing some of the highest levels of ambient outdoor NO_2. This is possible if individuals who are less concerned about air pollution levels selectively choose to live in London.

6.3.2 Biodiversity

The concept of biodiversity is complex and difficult to measure and operationalise in a consistent and meaningful way for health and well-being studies (Sandifer *et al.* 2015). In this thesis, I have used the Convention of Biological Diversity (CBD) definition for biodiversity as "the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species, and of ecosystems" (United Nations 1994).

In this thesis, I use several measures of biodiversity: species richness of butterflies, birds and plants, habitat diversity, NDVI standard deviation and site designation. The sites designation is Sites of Importance for Nature Conservation (SINCs), a London-specific system that highlights all areas that are considered to have important biodiversity. Overall, I find mixed results across the different measures of biodiversity. I find that living within a 1km walk of a SINC is associated with higher levels of life satisfaction (and that there is no relationship found between all public open spaces). I also find some evidence that neighbourhood-level butterfly and bird species richness, and NDVI standard deviation are associated with self-reported general health, but that there is no relationship with neighbourhood habitat diversity. These findings contribute to a small but growing body of literature that explores the relationship between biodiversity and well-being (Cameron *et al.* 2020; Dallimer *et al.* 2012; Fuller *et al.* 2007; Luck *et al.* 2011; Wood *et al.* 2018).

Recent reviews highlight that there does not appear to be any consensus on how biodiversity contributes to well-being, and the evidence base is too small and varied to draw any conclusions from (Lovell *et al.* 2014; Marselle *et al.* 2019). Across the literature, associations are often weak or contradictory. This likely reflects a number of key points regarding not only the relationship between biodiversity and well-being, but also in the approach and methods used to explore the relationship: how both biodiversity and well-being are defined and measured.

Broadly speaking, it is understood that biodiversity supports a number of key ecosystem services that support health and well-being, such as food production, providing raw materials for shelter, and improving recreational value (Aerts *et al.* 2018; Pascual *et al.* 2017). Another suggestion is that areas of higher biodiversity provide increased opportunities to interact with nature, providing psychological and physiological restorative benefits (Marselle 2019). However, as yet we still do not know what facets of biodiversity provide these potential benefits, and also what these benefits are.

The use of several different indicators of biodiversity in this thesis is an important contribution to this literature. When using species richness metrics, our results suggest a relationship between butterfly and bird species richness and self-reported general health. There was no relationship found with plant species richness or habitat diversity, which is using the Phase 1 Habitat survey methodology which is largely based upon the presence or dominance of certain plant species or plant characteristics. Previous research studies also find positive relationships with birds (Cameron *et al.* 2020; Fuller *et al.* 2007; Luck *et al.* 2011). There are several explanations for our findings. Birds are relatively easy to detect, and invoke several senses at one time through sound as well as sight. They may also be associated with common nature interaction activities such as domestic bird-feeding (Cox & Gaston 2016). Butterflies move and can be brightly coloured, and can therefore be easily detected by people (McGinlay *et al.* 2017). Many plant species will be difficult to detect and therefore will not contribute to how individuals respond to them.

However, contrary to our findings, previous studies have also found positive relationships with plant species richness (Fuller *et al.* 2007; Lindemann-Matthies & Matthies 2018) and habitat diversity (Cameron *et al.* 2020), no relationship with butterfly species richness (Dallimer *et al.* 2012; Fuller *et al.* 2007), and bird species richness (Dallimer *et al.* 2012; Taylor *et al.* 2018), and a negative relationship with plant species richness (Dallimer *et al.* 2012). There appears to be very little consensus within the literature regarding links between well-being and species richness and habitat diversity.

There are several problems with using specific species, taxonomic groups or habitat diversity as a measure of biodiversity in well-being studies. Biodiversity monitoring data have many known issues relating to biases in data collection e.g. observer bias, taxonomic bias (Isaac & Pocock 2015; Troudet *et al.* 2017). It is likely that the relationship between well-being and biodiversity is not linear. For example, previous research showed that people have a preference for intermediate levels of plant diversity (Lindemann-Matthies & Matthies 2018). It could be that places with high biodiversity are considered too wild, or that they contain species that are dangerous, and therefore are considered dangerous and unsafe to visit (de Vries & Snep 2019). It is also likely that not all species contribute equally to how an individual perceives biodiversity. Common bird species for example, such as pigeons, may not contribute equally to a more rare, colourful or tuneful species (Cameron *et al.* 2020). Conversely, certain rare butterfly species are also small and difficult to detect, so therefore rarity is not necessarily an important factor. Additionally, certain species that are invasive and represent a potential threat have been shown to have a negative association with well-being (Jones 2017). Some evidence suggests that abundance may be more important than richness (Cracknell *et al.* 2017). Functional or phenotypical traits may be more useful as they are more easily perceived by individuals, such as mobility, height of trees or colour of fish (Botzat *et al.* 2016).

In chapter 4 of this thesis, I use site designation as another proxy for biodiversity. Using sites designated as Sites of Importance for Nature Conservation (SINCs) identifies places that have significantly important biodiversity without requiring a specific objectively measured indicator of that biodiversity. It has been shown in previous studies that site designation is positively related with well-being (Garrett *et al.* 2019b; Wheeler *et al.* 2015; Wyles *et al.* 2019) and my findings also support this body of work. The positive and consistent findings across studies using this measure of biodiversity (or quality) suggests that there may not be one specific biological characteristic of a site that relates to well-being, but that there are a combination of factors together. It might be that individuals know they live in close proximity to an important natural site, providing them with a sense of well-being. Alternatively, the designation of these locations might lead to the surrounding residential locations to be highly desirable, therefore attracting individuals in higher socioeconomic groups to the area, who are found to have relatively higher levels of life satisfaction.

Many of the explanations relate to how biodiversity is perceived by an individual. There is a growing body of evidence that suggests how people perceive biodiversity is a better predictor of well-being than actual biodiversity measures (Dallimer *et al.* 2012; Schebella *et al.* 2019). However, there is mixed evidence to indicate how well individuals are able to accurately perceive actual biodiversity levels (Southon *et al.* 2018). Studies suggest that individuals are better able to accurately predict actual biodiversity levels the more connected to nature they are or if they perceive nature to be restorative (Carrus *et al.* 2015; Marselle *et al.* 2016; Martin *et al.* 2020; Richardson *et al.* 2018). Therefore, if higher perceived biodiversity levels are related to higher levels of well-being, it is important then to not only protect and increase actual biodiversity levels, but also to develop ways to improve how people perceive nature and how connected they feel to it.

It is clear that there are many different ways to characterise and measure the 'type' and 'quality' of green- and bluespaces. There are clear parallels across several of the land use categories and habitat types, such as Reservoirs and Still water, and the woodland categories, but the emphasis on use in the PPG17 typology differentiates itself from the habitat type dataset. The habitat types dataset also contains information about all the habitat types present within each land use category, which allows diversity metrics to be calculated. In chapter 5, I examine the relationships between PPG17 land use type categories and the biodiversity metrics, as well as mean NDVI as a measure of "greenness".

This analysis is important to attempt to understand how the ecological characteristics of different land uses play a part in delivering well-being benefits to individuals. This analysis highlights that within each PPG17 category itself there is a great variation in biodiversity.

6.4 Aim 3: To consider different ways of measuring proximity or exposure to the natural environment

In this thesis, I examined the relationship between well-being and the natural environment, based on each individual's residential location. I use two different levels of spatial resolution for residential location: LSOA (as an area and also its population-weighted centroid) and 6-digit postcode centroid. LSOAs are an administrative geography used to describe small area statistics, defined by population size (between 1000-3000) and household count (between 400-1200). Using the coarser LSOA location meant that neighbourhood area statistics could be calculated using a consistent, well-recognised and therefore comparable unit. Many covariates were also available at the LSOA level (e.g. Indices of Multiple Deprivation) and therefore spatially linking data was possible.

A postcode unit is much more spatially accurate, representing part of a street or an individual building (dependent on mail volume). The highly spatially accurate postcode-level data, provided as an easting and northing, was only accessible in the UK Data Service Secure Lab environment. Using this location data gave point locations of each individual for each wave, and was therefore a much more accurate representation of an individual's location than the LSOA code.

Despite the drawbacks of using administrative units as boundaries, the LSOA was a useful unit to analyse proximity and exposure within an individual's neighbourhood. An alternative could be to use buffer zones around the postcode centroid location, but this also has drawbacks, such as requiring decisions to be made regarding buffer size (Labib *et al.* 2020b). Neighbourhood units have been used widely in the literature that examines the relationship between well-being and the natural environment (Akpinar *et al.* 2016; Ambrey & Fleming 2013; Astell-Burt *et al.* 2014c; Wheeler *et al.* 2015; White *et al.* 2013b).

In chapter 4, I conduct the same analysis using both LSOA (population-weighted centroid) and postcode-level location. I find a significant relationship between well-being and living within 1km of a SINC found using the postcode-level location, but no significant association at the LSOA-level. The significant relationship between well-being and access to private open space remains in both levels of analysis. Given that the geographical location was only used to identify the proximity to SINCs and public open spaces (POSs), this suggests that conducting this analysis at the more generalised LSOA-level is not sufficient at capturing an individual's residential exposure to public natural spaces. This was surprising, given that LSOAs are generally small in London (mean size is 3.3 km^2, the mean for England is 4 km^2). This finding suggests that there are important differences in walking time and access to public open spaces across different locations within an LSOA, and that the population weighted-centroid location is not necessarily a useful proxy for residential location. The population-weighted centroid of an LSOA is an aggregation of all the population-weighted centroids of the underlying output areas (OAs) that make up an LSOA. Therefore, in reality there will be several locations within an LSOA which represent a residential node (Higgs &

Langford 2009). In previous work, residential location, rather than administrative centroid, is considered the gold standard in health research (Mizen *et al.* 2015).

I used three different methods to measure proximity or exposure to the natural environment: proportion in the residential neighbourhood, network analysis using a given distance threshold, and distance-decay functions. The former are commonly used in the well-being and nature literature, the latter is rarely used. Neighbourhood proportion, for example the LSOA, is again a consistent and easily comparable unit of analysis. This method assumes that an individual's exposure to the natural environment is best captured within this boundary. Realistically however, this is not likely to always be the case. LSOAs vary greatly in their shape (and in size, but less so in urban areas), and if an individual lives on the boundary of an LSOA, then it is reasonable to suggest that the individual is just as likely to use the neighbouring LSOA than the one they reside in. Another issue with the neighbourhood proportion method is that the value indicates the 'amount' of that entity within the unit, but not the location or composition (e.g. if an LSOA is comprised of 60% woodland, we do not know if that is one big woodland, or if that is 3 smaller woodland patches). Similarly, it does not indicate if that is the whole size of that entity or if the actual size is much larger (e.g. the part of the LSOA that is woodland is actually the edge of a much larger greenspace). This method therefore does not allow for the effect of the natural environment outside of the LSOA to be accounted for.

The network analysis method used to create the Areas of Deficiency layers used in chapter 4 effectively identifies all locations that are within a 1 km walk from an entrance point of a public open space. The postcode-level location could then be flagged as being either inside or outside these zones. This method removes the problems related to arbitrary boundary of the neighbourhood proportion method, and allows for all open spaces to be included in the exposure assessment. It also attempts to capture a more realistic pattern of how an individual might be exposed to the natural environment by using actual travel routes. However, this method does require the choice of a network distance, a similar problem to using buffer zones as neighbourhood units.

In chapter 5, I use both LSOA neighbourhood proportion and distance-decay functions to measure exposure. Distance-decay functions are rarely used in well-being and nature research and this provided an opportunity to not only test this method, but compare it to another exposure method. The results were surprisingly different between the two methods in this chapter. On explanation for this is that, quite simply, they are measuring different types of exposure. Distance-decay allowed all OSSs to be included in the exposure calculation, weighted by the Euclidean distance to them, whereas the LSOA proportion method includes only what is present in the LSOA. The distance-decay method calculated exposure to different biodiversity and habitat metrics of OSSs, whereas the neighbourhood method captured anything that fell inside the LSOA boundary.

Measuring the exposure to ambient outdoor air pollution in chapter 2 had specific methodological differences to that of green-and bluespaces. Green- and bluespaces are, arguably, discrete places, whereas air pollution is continuous across space. Therefore, methods that use distances (e.g. network analysis, distance-decay function) are not appropriate for air pollution exposure, unless distance from specific pollution sources is being examined. Neighbourhood statistics can be calculated, or pollution experienced at a specific residential location can be estimated. In this thesis, we used a modelled air pollution dataset which had used spatial interpolation methods to estimate pollution levels across space, providing estimates for each 1 km grid cell in the UK. This modelling accounted for a range of factors that affect air pollution dispersal, such as pollution sources, weather variables, and topology. Therefore, there is likely increasing spatial error in air pollution estimation, the further from a pollution sensor a location is.

A similar issue exists when examining biodiversity. Depending on how biodiversity is defined and measured, biodiversity is not a discrete phenomenon, it does not only exist within the boundaries of green- and bluespaces. Additionally, with the exception of plants, species are mobile. The specific location of a species siting corroborates its presence in that location, but it also does not confirm its absence in other locations. The operationalisation of biodiversity data in health and well-being studies needs to account for the complexities, shortcomings and assumptions that underlay species monitoring data.

In chapter 2, the analysis was conducted for England, whereas analyses in subsequent chapters were conducted for Greater London only. This effect of this change in spatial scale became pertinent when using LSOAs as neighbourhood units. LSOAs are by definition smaller in urban areas than rural areas, therefore LSOAs in the London analysis were not only smaller, but much less variable in size (mean size in London is 3.3 km^2, the mean for England is 4 km^2). This might be one of the reasons that in chapter 2 I find a significant relationship with NO_2 levels, but not in any of the later chapters. Perhaps the relationship between life satisfaction and LSOA-level green- and bluespace is different across levels of urbanity.

Similarly, a common assumption here, and in many similar studies, is that local natural environment conditions aggregated up to LSOA-level statistics are reasonable proxies for the relative exposure by local resident populations (Wheeler *et al.* 2015). LSOAs are likely to be heterogeneous in terms of the natural environment composition, and any estimations of exposure at the individual-level from aggregated statistics suffers from ecological fallacy issues and aggregation bias.

Ultimately, all exposure methods and geographical scales are subject to spatial error in the estimation of exposure to the natural environment. Whenever statistics are calculated using aggregated spatial data, the issues associated with the Modifiable Areal Unit Problem (MAUP) will affect the estimate (Dark & Bram 2007). This has implications for how best exposure to the natural environment is captured and quantified. For example, the size, shape and aggregation level used when neighbourhoods are the exposure unit, and the distance used when using buffer zones, will give different exposure statistics. Similarly, the dataset used to represent the natural environment will also introduce error into the estimate. For example, NDVI products of differing spatial resolutions, or the size and shape of green- and bluespaces. Moreover, recent research suggests that the shape, form, connectivity and complexity of open spaces might be significant in explaining variations in health and well-being benefits gained from the natural environment (Mears *et al.* 2019a; Tsai *et al.* 2016; Wang & Tassinary 2019).

6.5 Other considerations

6.5.1 Different sample populations differ in their relationship with the natural environment

In this thesis, I have used two panel datasets as population samples. I use two different longitudinal panel datasets, the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS), which are both available as part of the Understanding Society project (University of Essex *et al.*, 2014). The BHPS and UKHLS are large multi-year panel surveys collecting individual and household information from a representative UK sample population. Demographic, socio-economic, health and geographic data are collected in the dataset, as well as that pertaining to attitudes, opinions and values. Each individual has a geocoded spatial location assigned to them at each wave, which corresponds to their residential address. Using this spatial location has allowed me to spatially link data about the natural environment to each individual for every wave.

The construction of the BHPS and UKHLS instruments as prospective annual panels mean data is also collected much more reliably than long-term retrospective history surveys, which suffer from issues such as post-hoc rationalisation and contamination of memory (University of Essex 2016). Panel data creates continuous data through time about an individual. Panel data allows for analysis at the individual-level, which is different, for example, to repeat cross-sectional surveys which allow for population-level dynamics only to be measured. These are key strengths to using these two datasets in this thesis. Using panel data also allowed me to employ fixed effects regression. Fixed effects have a significant advantage over cross-sectional correlations as it allows the user to isolate within-person variation as opposed to between-person variation. I effectively follow the same individuals over time, thereby controlling for time-invariant omitted variables (e.g. personality traits), that could be related with both proximity to open space and subjective well-being. This is a considerable methodological improvement on much well-being and nature research, which predominantly uses cross-sectional data (Houlden *et al.* 2018). Several recent papers call for more longitudinal studies and the analyses in this provide a key contribution to the literature in this respect (Gascon *et al.* 2018; Houlden *et al.* 2018; Markevych *et al.* 2017).

Despite both the BHPS and UKHLS being representative samples of the UK population, they have underlying differences in their sampling structure, and therefore spatial distribution, and also their demographic composition and representativeness. These differences may partly explain why I find differing relationships between the two studies in chapters 3 and 5. One of the main differences between the BHPS and the UKHLS are the dates they were collected. The BHPS ran from 1991 to 2008 (waves 1-18) and the UKHLS from 2009 to the present day (waves 1-8 were available when writing). It is likely that over this time period, awareness of environmental issues has increased (e.g. climate change and biodiversity loss) and this might affect how individuals are affected by their surrounding natural environment. They also differ in size, the BHPS collected information from over 10,000 individuals (5000 households) whereas the UKHLS collected information from over 50,000 individuals (40,000 households).

The sampling structure of the BHPS means that the sample is more spatially clustered than the UKHLS. Both surveys have a clustered and stratified sampling design in their main sample for England (this is different to, for example, the Northern Ireland sample in the BHPS), but the BHPS participants are drawn from 250 primary sampling units, in contrast to over 3000 in the UKHLS.

Common to all panel surveys are trends in missing data, due to attrition (participants leaving the study), non-response, or by becoming ineligible (e.g. death, moving abroad). Conversely, people can also enter surveys, for example as new temporary sample members moving in and out of the survey (e.g. new cohabiting partners). Lynn and Borkowska, (2018) analysed attrition and representativeness across the waves of both the BHPS and UKHLS. They found that over the eighteen waves of the BHPS, the sample sees relatively low levels of attrition. For the BHPS, they find that 70% of the initial sample were still participating after 12 years. However, the number of individuals who interviewed at every single wave (i.e. a balanced panel) reduces to approximately half by wave 18. Attrition was greater amongst younger age groups, men, black people and participants on lower incomes.

They highlight that while the UKHLS main sample showed differentiated attrition in the same demographic groups, it had a higher attrition rate than the BHPS. While 78% of the BHPS sample were still participating after six years, only 52% of the UKHLS main sample were still participating after six years (Lynn & Borkowska 2018). This highlights important differences in demographic composition between the two surveys, and may in part explain some of the differences in results found between them. This might be important; several studies have highlighted the potential significance that individual characteristics play in the relationship between well-being and the natural environment. For example, the relationship between residential greenspace and mental distress was found to vary with age and gender in nine waves of the BHPS (Astell-Burt *et al.* 2014c). In another study, only those individuals in the lower socio-economic status category, as measured by education attainment, were found to have a significant association between well-being and surrounding greenspace (de Vries *et al.* 2003). Additionally, the >120minute physical activity threshold for achieving well-being benefits from neighbourhood greenspace was significant for the White British category but not for others, suggesting potential differences by ethnicity in relationships between natural spaces and health and well-being benefits in England (White *et al.* 2019). If those in younger age groups, men, black individuals and those with lower incomes are under-represented in both surveys, and more so in the UKHLS, it seems likely that this will contribute to different outcomes in the analyses.

Another difference between the BHPS and the UKHLS is in the interview mode used. The BHPS was predominantly collected using face to face interviews, whereas the UKHLS was collected in this way for waves 1 and 2, with possible changes in subsequent waves to include more telephone and web interviews. There is evidence to show that interview mode affects how individuals answer questions (Nandi & Platt 2017), and this also might partly explain some differences in our findings between the two surveys.

6.5.2 Different subjective well-being measures are associated with different characteristics of, and exposure to, the natural environment

In this thesis, I use up to three different measures of subjective well-being: life satisfaction, mental health (or mental distress), and self-reported general health. These three measures are some of the most commonly used questions/instruments in subjective well-being surveys and studies, and are considered highly reliable and consistent. Life satisfaction is a cognitive and evaluative measure of well-being, allowing the individual to rate their life in context and in comparison to other factors (Kahneman & Krueger 2006). This is different to the GHQ, which is an experiential and affective measure of recent experiences and is considered a marker of psychological distress (White *et al.* 2013b). Affect can be both positive and negative, and they are not necessarily opposite ends of the same spectrum. Like life satisfaction, self-reported general health is an evaluative measure, however it is asking the respondent to evaluate a different aspect of an individual's well-being. It requires the respondent to consider one's own state of health, which encompasses both physical and mental states.

The findings in this thesis suggest that the effect found between the natural environment and well-being varies between well-being measures. In chapter 4, I find a significant association between proximity to SINCs and life satisfaction, but not with mental distress (as measured by the GHQ), when controlling for the effect of having access to private open space. Additionally, in the other chapters, I find few categories of land use, habitat type and biodiversity where there are significant relationships with two or more well-being measures in the same survey (although there are several with two or more significant associations (e.g. Golf courses, Canals, and Road island/verges in chapter 3), and these are considered as strong evidence of a relationship).

These findings suggest that the three well-being measures are capturing different aspects of human well-being, and that some characteristics of the natural environment have an effect on certain well-being measures and not others. The use of three different measures of well-being in this thesis is useful because it has allowed a broader examination of the different ways the natural environment may be associated with our lives. The findings in chapter 4 are supported by other research that finds nature exposure has a stronger effect on positive rather than negative emotions (McMahan & Estes 2015; White *et al.* 2017).

The differential relationships may likely be underpinned by the different mechanisms and causal pathways that are suggested to explain the relationships found between well-being and the natural environment. We find some evidence of a relationship between several biodiversity measures and self-reported general health. This might be explained by biodiverse environments providing opportunities for increasing interaction with nature, providing psychological restorative benefits, or feelings of fascination. It might also support the microbiome theory, where health and diversity of the natural environment have been related to overall higher diversity of gut microbial composition and therefore a better functioning immune system (Hough 2014; Lai *et al.* 2019; Pearson *et al.* 2020; Sandifer *et al.* 2015). I find evidence that exposure to bluespace is associated with life satisfaction and mental health. This may be underpinned by feelings of psychological restoration, described by the Attention Restoration Theory and the Stress Reduction Theory. The negative association found in chapter 2 between NO_2 levels and life satisfaction may be via concern for one's own health and that of their family, or perhaps through how they perceive their neighbourhood. This supports the Stress Reduction Theory where a cleaner environment would lead to a reduction in stress levels.

6.5.3 How big are the effect sizes found?

Methodologically, this thesis makes some important contributions to the well-being and nature literature. I use longitudinal individual-level data which allows me to use fixed effects regression. The fixed effects model is useful for causal inference because it controls for all fixed characteristics, both observed and unobserved, that may confound the estimate of the effect of the natural environment on well-being. This is an improvement on cross-sectional approaches, whose coefficients will be biased by unobserved time invariant confounders, such as genetics, personality and experience. We observe this in chapter 2, where we use a standard OLS regression (ordinary least squares) to compare the estimate with fixed effects. The effect size for NO_2 is larger in the OLS model than in the fixed effects model, which reflects the importance of controlling for time-invariant unobserved heterogeneity.

Overall, the effect sizes found in this thesis are small. However when standardised coefficients are used I find that the effects are relatively comparable to that of other known determinants of subjective well-being, such as unemployment, having a health condition, and marital status. At an individual-level this is not trivial, and as these effects are likely to be experienced by many people (e.g. many people have access to public open spaces, and air pollution is experienced to some extent by everyone), the community-level implications of exposure to the natural environment are likely to be significant.

However, across all the models in this thesis, our R^2 values are relatively small (between R^2=0.03-0.12). This suggests that there is still a large amount of variance that is being unaccounted for in our models. However, this is extremely common in studies that explore individual-level well-being and reflects the complexity in capturing the determinants of well-being in humans (White *et al.* 2013a, 2013b). This unaccounted heterogeneity in our models may be explained by time-varying omitted variables in our model specifications. Experiments such as random control trials further address this issue of unaccounted error, but were not possible in this thesis. Quasi-experimental analytical design methods such as instrumental variable modelling also allow this, and this method was used in chapter 2. It is very difficult to find suitable instruments in the analysis of the relationship between the natural environment and well-being. The instrument must be related to changes in the natural environment but not with subjective well-being, for example a discrete event such as a policy change.

The most important determinant of our confidence that the effect estimate is causal is whether the change in exposure to the natural environment is plausibly unconfounded (Strumpf *et al.* 2017). In this thesis, I include a suite of explanatory variables in my model specifications to control for heterogeneity in the model. The use of key individual- and neighbourhood-level control variables captures important differences in the economic, social, and environmental conditions that are likely to affect both subjective well-being and the natural environment. Fixed effects controls for any time-invariant omitted variable bias in the model specifications. However, to be able to confidently assert a causal relationship, we have to be sure that any changes in exposure within an individual are effectively random. Unaccounted time-varying factors and reverse causality remain a concern in these models. For example, it might be that individuals with higher levels of subjective well-being choose to move to places that are greener (or bluer), or that those who feel more connected to nature, and therefore potentially more affected by nature, chose to live in locations where they can access green- and bluespaces easily. Those individuals who are wealthier or have a higher socio-economic status are more likely to move to places with higher levels of biodiversity for example, known as The Luxury Effect (Leong *et al.* 2018). While I attempt to control for some of these factors, using household income and deprivation metrics as control variables, and fixed effects controls for individual-level factors that do not change through time, it is likely that there are other sources of heterogeneity in the model that bias our estimates.

6.5.4 Problems with multiple testing

Throughout the thesis, multiple testing is used to explore the data and address research hypotheses. Multiple testing has significant benefits such as enabling exploratory analysis on many environmental variables. However, multiple testing, or simultaneous statistical inference, leads to increased probability of type 1 errors (false positives). This means the conclusions drawn in this thesis about specific landcover/land-use and habitat associations with $p<0.05$ coefficients might be a little overstated. Being mindful of this, the results in chapters 3 and 5 can be described as exploratory results, as per Bender & Lange (2001). One possible way to correct for issues related to multiple testing could be to increase the significance threshold, for example from $p<0.05$ to $p<0.001$. Another technique could be the statistical adjustment for multiple testing, for example the Bonferroni procedure. Both suggested approaches would reduce the probability of achieving type 1 errors, however they also reduce the probability of achieving true positives. A less conservative approach that might be used in future work could include False Discovery Rates (FDMs). Like the previous methods, FDMs statistically adjust p-values for multiple testing, but they reduce the rate of false positives within the statistically significant results only.

6.6 Limitations and recommendations for future work

One of the most important limiting factors of this analysis is the lack of longitudinal data pertaining to the natural environment. Air pollution data is the exception here, which has leant itself to an exciting analysis opportunity. However green- and bluespace data is very nearly always cross-sectional, reflecting one snapshot in time. Even datasets that have several years' worth, or repeating snapshots, such as the UK Land Cover Map, are based on different technology and methodology that they are not comparable across time. This is the benefit of using indices calculated from remotely sensed imagery, such as NDVI, as these are consistently calculated indices and can be compared over time, and they cover large spatial areas. However, care must be taken when making comparison across instruments, with different resolutions. A key recommendation for future work would be to identify longitudinal data relating to the natural environment. Land use databases should save previous versions so that change over time can be calculated. Alternatively, opportunities for data collection before and after an intervention or policy change allow for exciting experimental situations.

In chapter 4, I examine the role of private domestic open spaces on subjective well-being. This data was a binary variable indicating if the individual had access to a private open space. Data regarding the composition of private and domestic open space such as proportion of green, blue and grey, and information regarding biodiversity levels, and how these relate to different measures of well-being is an important next step in understanding further this relationship. Further key questions relating to natural environment data are identifying important combinations of habitat type or category and assessing if types in combination are important for well-being. For example, open spaces with both green and blue habitats within them; this was found to be preferential for individuals looking at photos (White *et al.* 2010), and would be insightful for future open space planning. Further recommendations for biodiversity and well-being studies are to carry out more studies using accepted ecological measures of biodiversity (richness, abundance and diversity), as well as looking at the differential importance of certain species (e.g. rare or charismatic) or functional traits such as colour. There is a greater level of consensus across studies that shows a relationship between perceived, as opposed to actual, biodiversity and well-being, so further work should measure this, and indeed control for this when observing the relationship between well-being and actual biodiversity. An important consideration then is how to better engage with individuals to improve their perceptions of biodiversity, with the end goal of improving individual well-being.

This thesis uses England and then London as its case study locations, this is done for several reasons. There is a wealth of individual-level data available for the UK, which allowed me to employ statistical methods that were suitable for longitudinal well-being data. Several explanatory variables were only available for England, which then limited the extent of the study. To continue to use individual-level data, it invariably makes studying multiple countries difficult. Likewise, data pertaining to the natural environment generally improves in quality and resolution, and therefore accuracy, the smaller the spatial scale. This explains why my later chapters focus on one city, London. We cannot be sure if our findings found here for London will apply more broadly to other large urban areas similar to London, such as other English cities and those across the Global North. Despite Londoners enjoying greater access to public greenspace than the national average, 44% of Londoners living within a five-minute walk of a park, compared to 28% of people across Britain (Office for National Statistics 2020b), Londoners have just 18.96 m^2 of provision per person, which is almost half the national average (Fields in Trust 2020). Additionally, recent research also revealed that 1 in 5 Londoners do not have access to a private garden, which is higher than the national average at 1 in 8 for British households (Office for National Statistics 2020b). These findings potentially make the relationship between well-being and open space in London relatively unique in the country.

We also cannot say how our findings might translate to rural areas. Evidence shows those in urban areas gain fewer benefits from the environment than those in rural areas (Lapointe *et al.* 2020), and that Londoners are more likely to use greenspaces to meet with friends, and less likely for dog-walking, than those outside of London (Fields in Trust 2018). Selection bias may also be that those seeking to live in the capital are those who are least concerned about exposure to the natural environment, and therefore least affected in terms of their well-being. It is also not clear if these findings would apply in other parts of the world, for example those with vastly different levels of biodiversity, is unknown. It is recognised that much research that observes well-being impacts of the natural environment is conducted in the Global North, and therefore there is a definite bias in our understanding. Studies are emerging from tropical regions (Nath *et al.* 2018) and the Global South (Navarrete-Hernandez & Laffan 2019), but this thesis does not contribute to this area. Important future work could include conducting this research in different cities to assess to the extent to which the findings in this thesis apply to other urban areas.

In this thesis I examine residential proximity to the natural environment, but the 'use' of natural environments, such as frequency of visits or dose-response, is not considered. Neighbourhood determinants of well-being have been shown to be significant for residents, and also infer use either through indirect use or unintentional use. It has also been shown that natural environments close to the home are used more frequently than those further away. Future work could examine how residents in different neighbourhoods use and access their local green- and bluespaces, and how they also use public open spaces that are further away, and also their own private domestic spaces. This could be captured using qualitative research methods or mobile technologies. Better understanding how open spaces at differing distances from an individual's residence contribute to well-being, and if there are certain site characteristics that become important, or more important, the closer they are. Additionally, we do not consider the natural environment of other significant locations, such as workplaces. Evidence suggests that green infrastructure in central London provides well-being benefits for local workers (Cinderby & Bagwell 2018), and this exposure may influence that individual's well-being response to their residential natural environment. Improvements in mobile technologies are starting to allow for this holistic exposure measurement to be captured (Bell *et al.* 2015b; Kondo *et al.* 2020; MacKerron & Mourato 2013), and will provide opportunities for important future research.

Several studies have highlighted the potential significance that individual characteristics play in the relationship between well-being and the natural environment. For example, gender (Annerstedt *et al.* 2012), socio-economic status and protected characteristics such as BAME status and disabilities (Boyd *et al.* 2018). Additionally, there is some evidence to show that individual's preferences, beliefs and perceptions about nature and biodiversity are important to consider too, such as nature connectedness and perceived habitat and biodiversity (Pett *et al.* 2016; Schebella *et al.* 2019). An important continuation of this work would be to explore for any differential relationships based on individual characteristics through mediation and moderation analyses. This could be carried out using Structural Equation Modelling, and would also help us better understand the differences found between our two surveys. The biodiversity findings suggest that the relationship found with nature might extend beyond seeing nature, to also hearing it too. Other studies also suggest that nature connectedness involves developing a sensitivity to nature, in an affective way, to truly leverage well-being benefits from exposure to nature (Richardson & McEwan 2018). It is also likely that factors relating to seasonality, weather and noise affect this relationship (Boyd *et al.* 2018; Krekel & MacKerron 2020; Morckel 2015; Ojala *et al.* 2019). Further quantitative and qualitative research is needed to explore the implications of this and to enable recommendations for future interventions.

Important future work would be to measure and compare the error between using different units of location, such as LSOA and postcode centroids. A sound initial comparison could be made in chapter 5 by using LSOA population-weighted centroids in the distance-decay analysis, instead of LSOA proportion. Future work could use statistical methods that identify, and even better, correct for, spatial autocorrelation in the dependent and independent variables. It could be that there are spatial variations in the relationship between the natural environment and well-being (Giles-Corti *et al.* 2008; Labib *et al.* 2020b). A small number of studies have used techniques to explore and address this. For example, Houlden et al., (2019b) employed Geographically Weighted Regression (GWR) to account for statistically significant spatial clustering of model residuals found between greenspace and well-being across London. They found stronger positive association in the North, South and West of London, and less so in the East. They also find strong positive associations nearer the edge boundary of London, with weaker and sometimes negative associations in central London. They suggest these relationships may be explained by the different composition of greenspace in these areas. In a separate paper, Houlden et al., (2019a) use Spatial Error models instead of GWR to account for spatial variation in the relationship between life satisfaction and green- and bluespaces in London. This method uses a spatial weights matrix which accounts for patterns in subjective well-being that are not predicted by the explanatory variables, but are related to that of nearest neighbours. The further use of spatial models in the study of well-being and green- and bluespaces work should be given a high priority.

6.7 Concluding remarks

Despite the growing body of evidence that shows exposure to the natural environment is associated with a range of health and well-being benefits, better understanding of how to accurately quantify and compare the effect size of this relationship is a key research priority. Comparative studies are difficult given the breadth of well-being measures, natural environment metrics, analytical techniques and spatial units applied (Zhang & Tan 2019). Consequently, it is then difficult to gain consensus and proceed with recommendations and implementations for policy and behavioural interventions and guidance.

"There are opportunities to improve health through the choices government, regulators, businesses and individuals make in creating and contributing to healthier, greener and more accessible environments" (Environment Agency 2020). Recommendations regarding individuals' exposure to the natural environment already exist in the UK. For example, the UK Government recommends that individuals should be provided with an accessible, natural greenspace of at least 2 ha in size, within a 300m walk of their home (Natural England 2010). However, there are key evidence gaps in the understanding of the relationship between the natural environment and individual well-being measures, such as how the type of natural environment, environmental quality and biodiversity contribute, as well as exposure mode (Defra 2017). Land use strategy designed for improving well-being should consider the complex pathways between how different types of open space differentially effect individuals through different well-being metrics.

Overall, future work in this area should include measures of the *quality* of the natural environment, operationalised in robust and reproducible ways. For example, by using consistent land cover and land use typologies and well understood metrics of biodiversity. The subjective well-being measures used should be collected using standardised measures and scales to allow for effective comparison across studies. Further priorities include identifying ways to reduce the potential effects of estimation error in models, by reducing bias due to observed and unobserved time-variant heterogeneity, selection bias and ecological fallacy in spatially aggregated data. Analytical techniques employed should aim for longitudinal and experimental designs, or quasi-experimental designs such as instrumental variables regression. The use of large population sample data is important, as well as accounting for key covariates. There is still much to understand in how exposure is best measured, and spatially explicit models are likely to be a useful tool here. Comparative studies across locations are needed to observe trends in different global contexts and cultures, and the examination of inequalities in exposure is particularly urgent.

In this thesis, I find several important relationships between characteristics of the natural environment and subjective well-being. The effect sizes are small at the individual-level, although they are comparable to other determinants of well-being, such as reporting a health condition. However, even if the benefits of a particular form of contact with the nature environment are small, public investment may still be justified if there are benefits across a wide range of other policy domains (Defra 2017; Hartig *et al.* 2014). If the benefits achieved through exposure to the natural environment are moderated by how connected and interested people are with nature (Richardson & McEwan 2018), and high quality natural environments are associated with higher levels of well-being, then ultimately the key questions for future work should be how to provide accessible and high quality natural spaces and places to people, and how to increase individuals' connection with the natural environment. This is particularly important amongst demographics who are particularly disconnected or stand to gain the most from increased quality of, and connection to, nature. Enabling access to good quality natural environments is not necessarily about provision alone, but also involves community organisations and health service interventions such as social prescribing (Husk *et al.* 2020) to leverage any potential health and well-being benefits across society.

Appendix

Table S3.7.1. The number of polygons and percentage cover of each PPG17 open space category and subcategory (calculated using the GiGL Open Space Sites (OSS) dataset).

PPG17 category	# of polygons	% London area	% all OSS sites	Primary use subcategories	# of polygons	% London area	% all OSS sites
Parks and gardens	1532	5.82%	14.95%	Park	991	5.46%	14.02%
				Formal garden	532	0.33%	0.85%
Natural and semi-natural urban greenspaces (inc. urban woodland)	741	5.54%	14.23%	Common	70	1.06%	2.72%
				Country Park	23	0.72%	1.84%
				Private woodland	145	0.52%	0.83%
				Public woodland	141	0.76%	1.96%
				Nature reserve	360	2.68%	6.87%
Green corridors	1563	3.58%	9.19%	River	195	1.71%	4.40%
				Canal	48	0.17%	0.44%
				Railway cutting	237	0.79%	2.02%
				Railway embankment	170	0.42%	1.08%
				Disused railway/trackbed	13	0.02%	0.05%
				Road island/verge	823	0.36%	0.93%
				Walking/cycling route	74	0.11%	0.27%
Outdoor sports facilities	1394	6.74%	17.31%	Recreation ground	423	1.15%	2.95%
				Playing field	570	2.17%	5.56%
				Golf course	118	2.85%	7.31%
				Other recreational	279	0.57%	1.46%
Amenity	3803	4.08%	10.47%	Amenity green space	792	0.50%	1.28%
				Village green	18	0.03%	0.07%
				Hospital	56	0.26%	0.68%
				Educational	1128	1.61%	4.13%
				Landscaping around premises	1763	1.15%	2.96%
				Reservoir	46	0.53%	1.36%
	257	0.05%	0.12%	Play space	226	0.04%	0.10%

PPG17 category	# of polygons	% London area	% all OSS sites	Primary use subcategories	# of polygons	% London area	% all OSS sites
Provision for children and young people				Adventure playground	22	0.01%	0.01%
				Youth area	7	0.00%	0.01%
Allotments, community gardens and city farms	776	0.63%	1.63%	Allotments	672	0.60%	1.54%
				Community garden	88	0.01%	0.03%
				City farm	16	0.02%	0.06%
Cemeteries and churchyards	430	0.87%	2.22%	Cemetery/churchyard	430	0.87%	2.22%
Other urban fringe	797	8.06%	20.68%	Equestrian centre	103	0.46%	1.18%
				Agriculture	668	7.56%	19.42%
				Nursery /horticulture	26	0.03%	0.09%
Civic spaces	221	0.06%	0.16%	Civic/market square	150	0.03%	0.08%
				Other hard surfaced areas	70	0.03%	0.08%
Other	692	1.95%	5%	Sewage/water works	31	0.30%	0.77%
				Disused quarry/gravel pit	16	0.17%	0.44%
				Vacant land	491	0.82%	2.11%
				Land reclamation	10	0.15%	0.38%
				Other	143	0.51%	1.31%
No category	425	1.58%	4.07%	No category	447	1.63	4.19%
PPG17 subsets							
All open spaces					12,184	37.38%	100%
All green and bluespaces					11,878	36.7%	98.23%
All green spaces					11,589	34.29%	92.03%
All bluespaces					289	2.41%	6.2%

Table S4.1. Public open space (POS) categorisation according to The London Plan (Table 7.8 in The London Plan pp315.

Open Space categorisation	Size Guide-line	Distances from homes
Regional Parks Large areas, corridors or networks of open space, the majority of which will be publicly accessible and provide a range of facilities and features offering recreational, ecological, landscape, cultural or green infrastructure benefits. Offer a combination of facilities and features that are unique within London, are readily accessible by public transport and are managed to meet best practice quality standards.	400 hectares	3.2 to 8 kilometres
Metropolitan Parks Large areas of open space that provide a similar range of benefits to Regional Parks and offer a combination of facilities at a sub-regional level, are readily accessible by public trans-port and are managed to meet best practice quality standards.	60 hectares	3.2 kilometres
District Parks Large areas of open space that provide a landscape setting with a variety of natural features providing a wide range of activities, including outdoor sports facilities and playing fields, children's play for different age groups and informal recreation pursuits.	20 hectares	1.2 kilometres
Local Parks and Open Spaces Providing for court games, children's play, sitting out areas and nature conservation areas.	2 hectares	400 metres
Small Open Spaces Gardens, sitting out areas, children's play spaces or other areas of a specialist nature, including nature conservation areas.	Under 2 hectares	Less than 400 metres
Pocket Parks Small areas of open space that provide natural surfaces and shaded areas for informal play and passive recreation that sometimes have seating and play equipment.	Under 0.4	Less than 400 metres
Linear Open Spaces Open spaces and towpaths alongside the Thames, canals and other waterways; paths, disused railways; nature conservation areas; and other routes that provide opportunities for informal recreation. Often characterised by features or attractive areas which are not fully accessible to the public but contribute to the enjoyment of the space.	Variable	Wherever feasible

Figure S5.1 Habitat dataset of Greater London, as maintained by Greenspace Information for Greater London CIC (GiGL) [obtained 12th December 2018].

Table S5.1. Habitat codes and types – London Phase 1 typology (GiGL Data Guide Book).

Habitat name	Habitat description
ACDG Acid grassland	Un- or semi-improved grassland on acidic soils, with less than 25% cover of heather or dwarf gorse. Excludes reedswamp (17). Usually with one or more of Deschampsia flexuosa, Molinia caerulea, Nardus stricta, Juncus squarrosus, Galium saxatile, Potentilla erecta or Rumex acetosella in abundance.
ALTA Allotments	Communal allotment gardens which are under cultivation. Code disused plots under other habitats as appropriate.
AMNG Amenity grassland	Usually frequently mown, species-poor mesotrophic grassland characteristic of parks and sports pitches, containing similar species to 11. Scattered trees and shrubberies in parks should be coded separately.
ARBL Arable	Cropland, horticultural land (excluding allotments), freshly ploughed land and livestock paddocks stocked so heavily as to have little vegetation.
BASG Chalk grassland	Un- or semi-improved grassland containing calcicoles. Usually with some of Brachypodium pinnatum, Bromopsis erecta, Heliotrichon pratense, Thymus polytrichus, Sanguisorba minor, Centaurea scabiosa or Origanum vulgare in some abundance.
BATH Bare artificial	Includes tarmac, concrete, railway ballast, gravel paths, buildings and artificial margins to aquatic habitats, where these are minimally vegetated.
BOGG Bogg	Dominated by Sphagnum mosses (greater than 50% cover) with water table at or just below the surface.
BRAK Bracken	Stands where bracken is dominant. Also used with other habitat codes to indicate scattered bracken.
BSAR Bare ground	Includes active quarries, fresh road workings, spoil or tipping and earth banks of water habitats, where these are minimally vegetated. Excludes arable land.
CONW Conifer woodland	Woodland with coniferous species (incl. yew) comprising of at least 75% canopy.
DTWF Ditch	Distinguished by their (often agricultural) drainage role. Always code vegetated margins separately and note trophic status and whether saline or tidal.
FNCR Fen carr	Woodland or scrub over herbaceous vegetation with the water table above ground for most of the year.
HINA Not available	Areas which cannot be observed due to restricted access, etc.
HTHL Heathland	Dwarf-shrub cover greater than 25% of species such as heathers and Ulex minor, with less than 50% cover of Sphagnum. May include a large amount of acid grassland in a close mosaic, but code as a mixture if grassland areas are large.
IMSS Intertidal mud, sands	Intertidal areas without significant vegetation of higher plants. Try to record the extent at low tide.
IRAG Improved agricultural grassland	Species-poor mesotrophic grassland containing little but Lolium perenne, Trifolium repens, Agrostis species, Bellis perennis, Taraxacum and Ranunculus species. Distinguished by its agricultural use and hence usually less frequent mowing.
NHRG Herb-rich grassland	Mesotrophic grassland with more forbs typical of old grassland than 09. Likely to contain one or more of Primula veris, Lychnis flos-cuculi, Achillea ptarmica, Silaum silaus, Succisa pratensis, Stachys officinalis, Serratula tinctoria, Ophioglussum, Gensita tinctoria, Sanguisorba officinalis or Caltha palustris, or

Habitat name	Habitat description
	an abundance of Carex ovalis, Pimpinella saxifraga, Conopodium majus, Cardamine pratensis, Knautia or Filipendula ulmaria.
NNBW Non-native woodland	Woodland with non-native broadleaved species (incl. sycamore and sweet chestnut) comprising of at least 75% canopy.
NNHD Non-native hedge	Line of shrubs, with or without treeline, one or two mature shrubs wide (wider belts should be coded as scrub or woodland), with non-native species comprising at least 75% of the shrubs.
NSIG Semi-impr grassland	Mesotrophic grassland usually with one or more of Arrhenatherum elatius, Deschampsia cespitosa, Alopecurus pratensis, Cynosurus cristatus, Dactylis glomerata, Festuca arundinacea or F.pratensis. Contains more than just Lolium perenne, Trifolium repens, Rumex acetosa, Taraxacum, Bellis perennis and Ranunculus species, but lacks characteristic forbs. Excludes reedswamp.
NTSV Not surveyed	Not surveyed
NVBW Native broadleaf woodland	Woodland with native broadleaved species (excl. sycamore and sweet chestnut) comprising of at least 75% canopy.
NVHD Native hedge	Line of shrubs, with or without treeline, one or two mature shrubs wide (wider belts should be coded as scrub or woodland), with native species comprising at least 75% of the shrubs.
NWAS Woodland & scrub	Woodland and scrub (aggregated NVC)
ORCH Orchard	Planted fruit or nut trees forming at least 50% canopy cover.
OTHR Other	To be avoided if possible. Must be specified if used.
PLSH Shrubbery	Dominated (at least 75% cover) by shrubs, usually non-native species, the majority of which have clearly been planted. Excludes hedges (25, 34).
RDEP Ruderal	Communities composed of pioneer species such as occur in early succession of heavily modified substrates. Typical species include Senecio squalidus, S.vulgaris, Sinapis arvensis, Poa annua, Hirschfeldia incana and species of Polygonum, Persicaria, Melilotus, Atriplex, Chenopodium, Medicago, Vulpia, Picris, Lactuca, Diplotaxis, Conyza and Reseda.
RDSW Reedswamp	Stands of Phragmites australis with at least 75% cover of reeds. Includes dry and tidal stands.
RGHL Roughland	An intimate mix of semi-improved neutral grassland, tall herbs and scrub. If these occur in large enough patches they should be coded separately.
RWRS River	Rivers and streams. Always code vegetated margins separately and note trophic status and whether saline or tidal.
SCRB Scrub	Dominated (at least 75% cover) by shrubs (usually less than 5 metres tall), excluding fen carr, heathland, young woodland, coppice, hedges and planted shrubberies. Includes stands of hawthorn, hazel (except coppice with standards), elder and Salix cinerea, caprea and viminalis regardless of height.
SCTR Scattered trees	Trees forming less than 75% canopy cover over another habitat (excluding coppice with standards, which is coded as woodland). Record percentage tree cover here, and the rest of the area under the appropriate habitat.

Habitat name	Habitat description
STMS Saltmarsh	Intertidal areas appreciably vegetated with higher plants, excluding reedswamp.
STWC Still water (incl. canals)	Lakes, reservoirs, pools, wet gravel pits, ponds, canals, docks and brackish lagoons beyond the limit of swamp or wet marginal vegetation. Always code vegetated margins separately and note trophic status and whether saline or tidal.
TLHB Tall herb	Stands of tall non-grass herbaceous species, often rhizomatous perennials, such as Fallopia japonica, Conium maculatum, Chamerion angustifolium, Anthriscus sylvestris, Urtica dioica, Epilobium hirsutum, Solidago canadensis and species of Aster and Heracleum. Excludes herbaceous fen vegetation.
TYSW Swamp	Stands of Glyceria maxima, Typha species or Phalaris arundinacea where these species form at least 75% cover.
VEGW Vegetated walls	Includes ruins, fences and other artificial structures with an appreciable amount of vegetation (including mosses and lichens) but excluding artificial water margins, which should be coded as wet marginal vegetation if vegetated.
WOOD Woodland	Woodland (aggregated NVC)
WTMV Wet marginal	Emergent vegetation with a permanently high water table in strips less than five metres wide on the margins of water bodies. Contains species such as Iris pseudacorus, Apium nodiflorum, Acorus calamus and species of Rorippa, Alisma and Juncus. May include Phragmites, Typha and Glyceria maxima, but where these form single-species stands code differently. Usually too small to map but must always be coded if present.

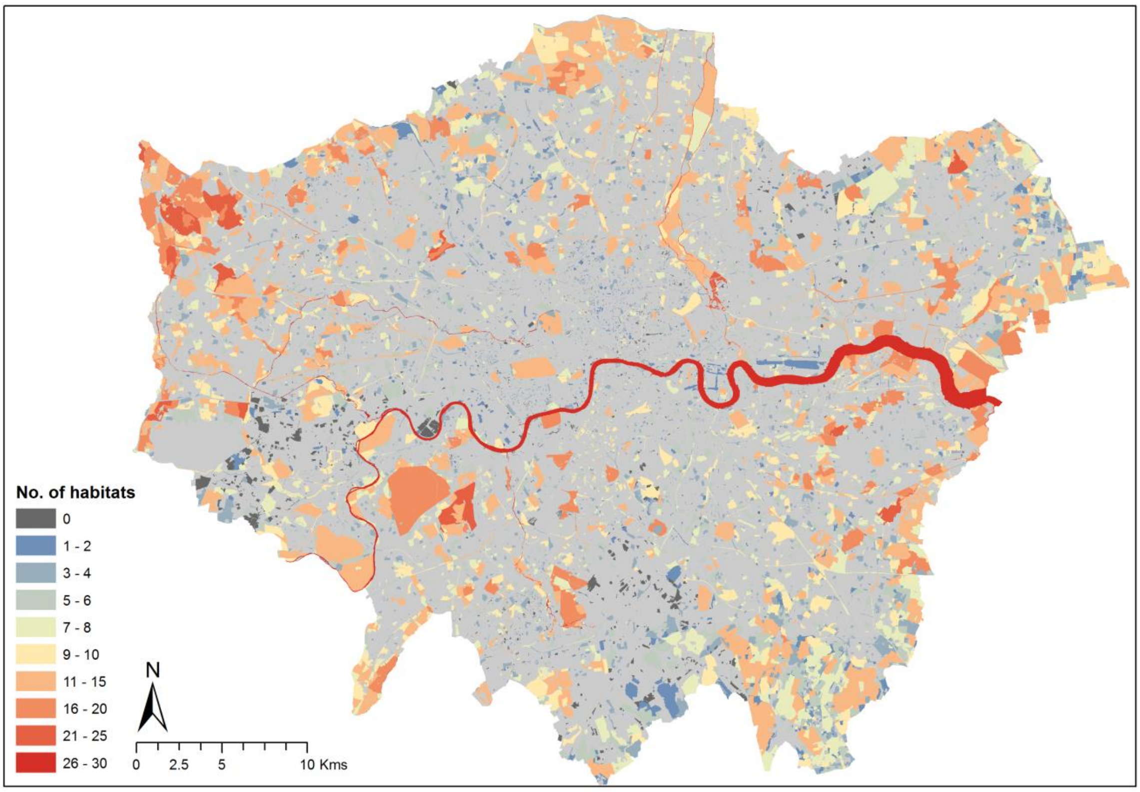

Figure S5.2. The number of habitats per Open Space Site (OSS) in Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

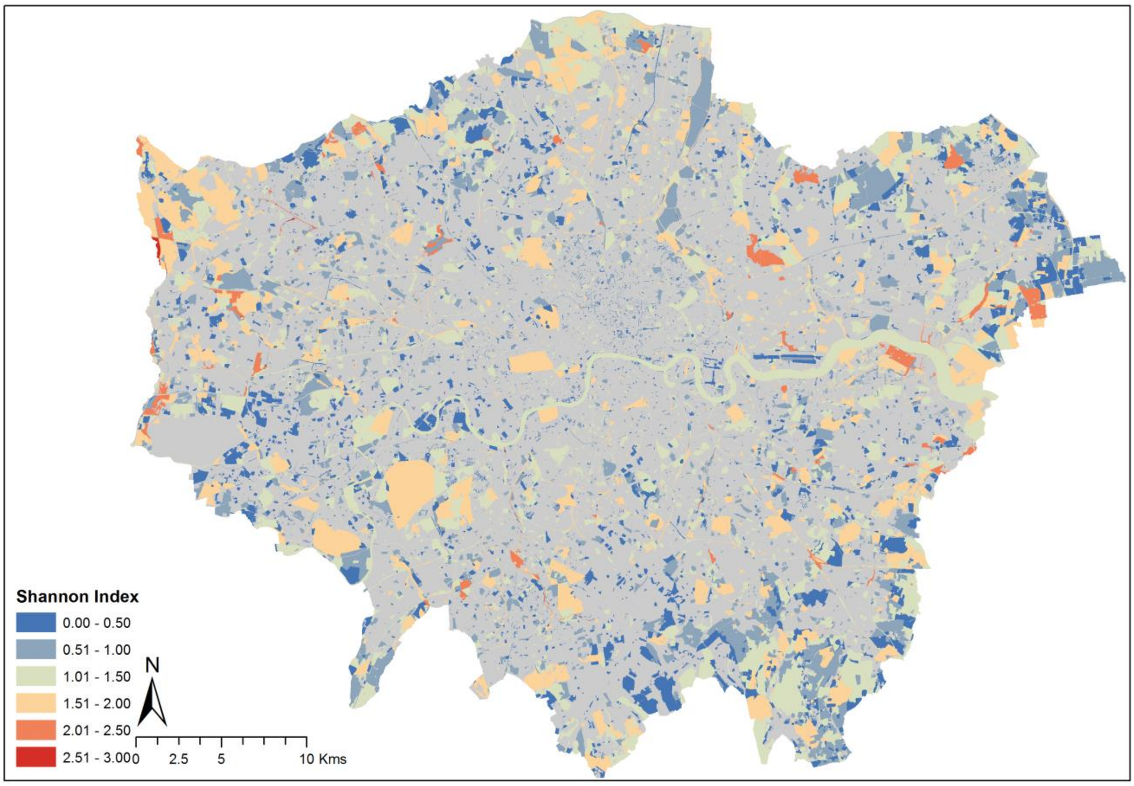

Figure S5.3. Shannon's Diversity Index per Open Space Site (OSS) across Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

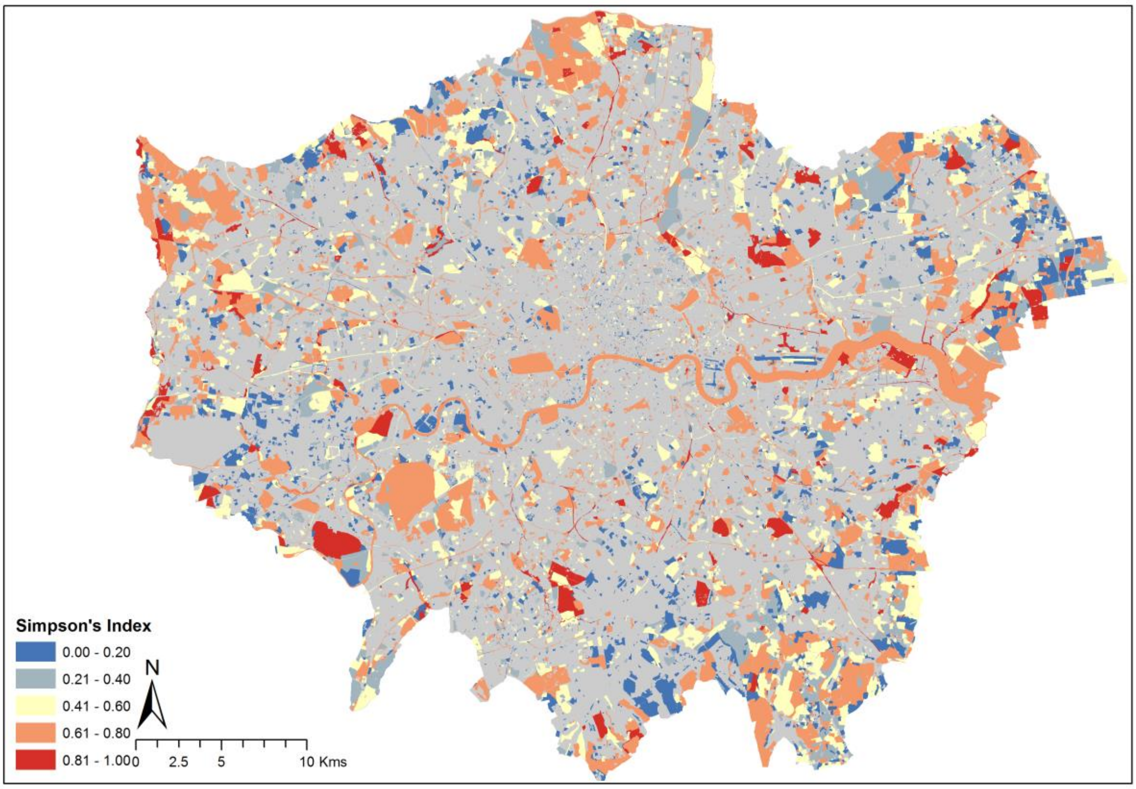

Figure S5.4. Simpson's Diversity Index per Open Space Site (OSS) across Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

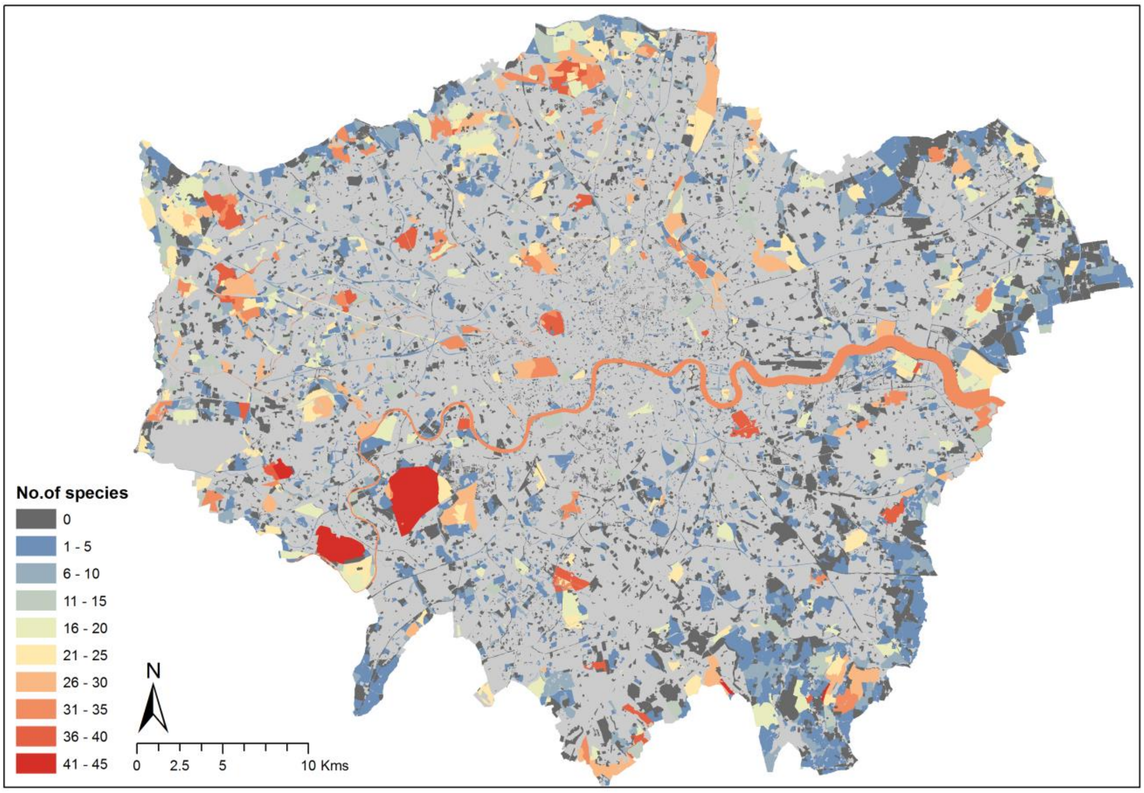

Figure S5.5. The number of butterfly species per Open Space Site (OSS) across Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

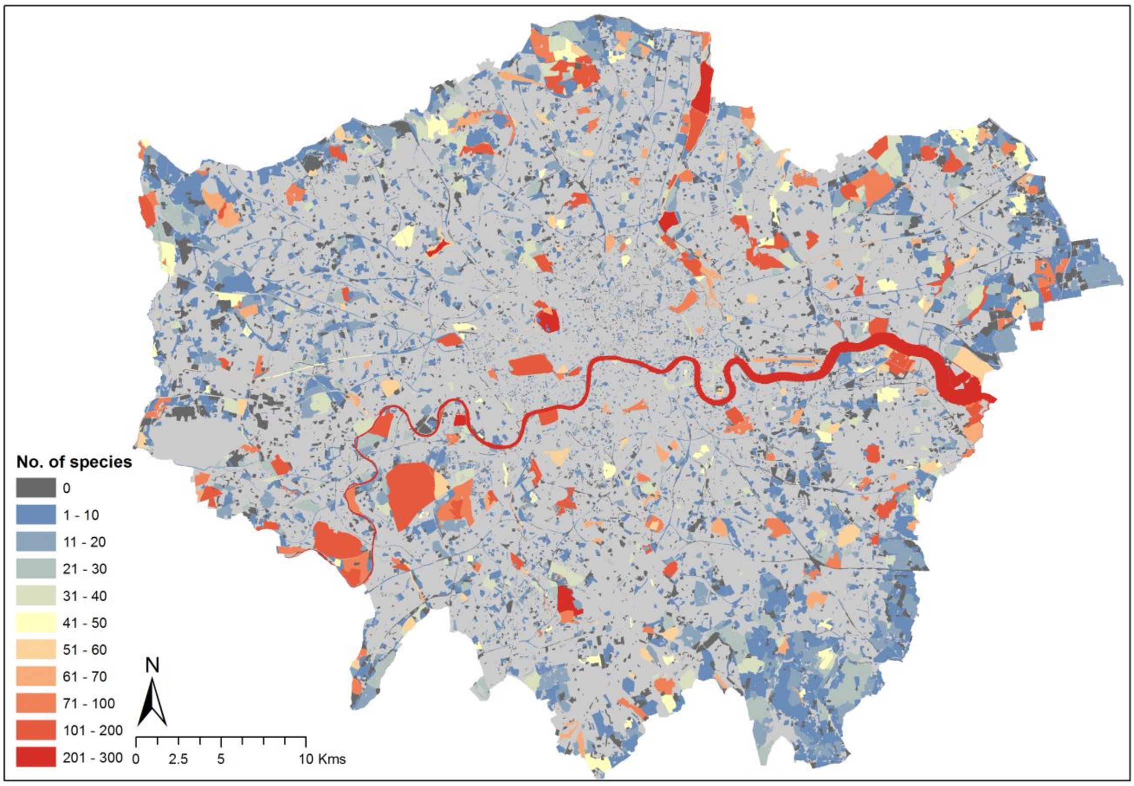

Figure S5.6. The number of bird species per Open Space Site (OSS) across Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

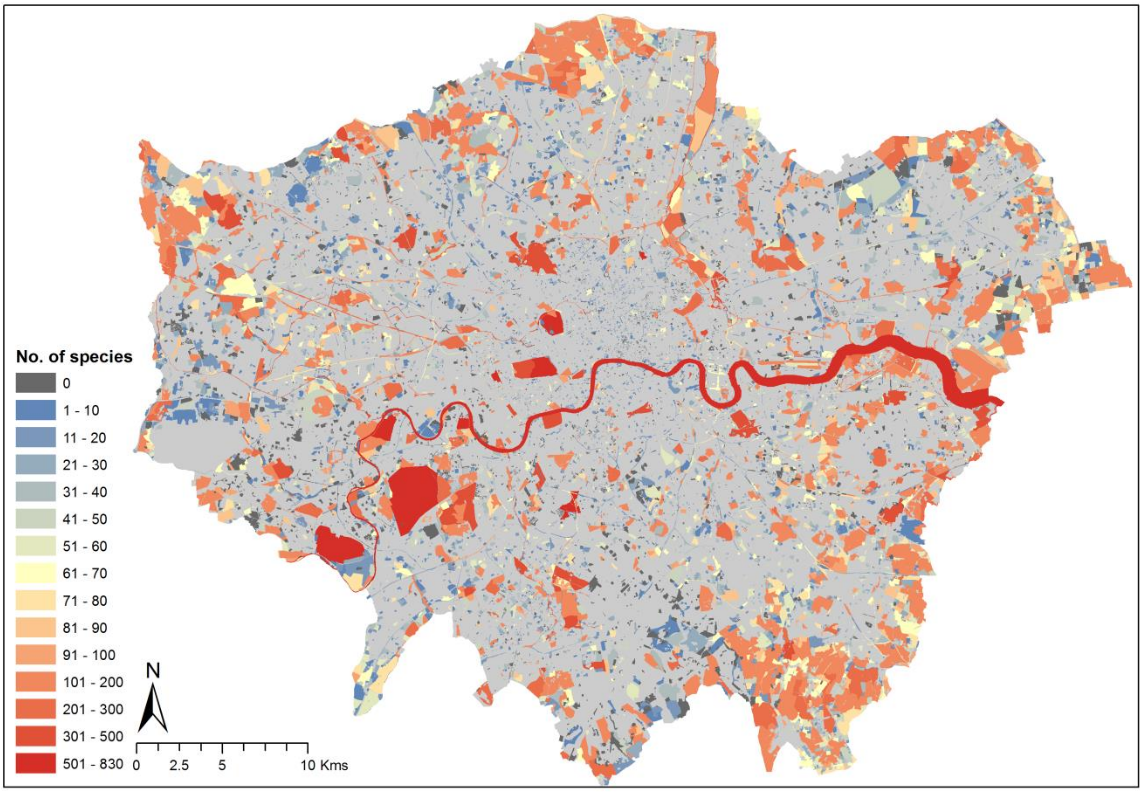

Figure S5.7. The number of plant species per Open Space Site (OSS) across Greater London. Data derived from Greenspace Information for Greater London CIC (GiGL) data [obtained 12th December 2018].

Table S5.2. LSOA-level regression results, showing unstandardised coefficients (full results from All OSS model).

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All OSS	0.001 (0.001)	-0.004 (0.005)	0.001 (0.001)	0.001 (0.001)	0.001 (0.004)	0.001 (0.001)
Habitat types						
ACDG Acid grassland	0.008 (0.010)	0.010 (0.035)	-0.006 (0.005)	-0.006 (0.016)	-0.003 (0.054)	0.005 (0.008)
ALTA Allotments	**0.042**** **(0.016)**	**-0.144*** **(0.059)**	0.001 (0.009)	-0.008 (0.013)	0.003 (0.043)	0.005 (0.007)
AMNG Amenity grassland	0.003 (0.003)	-0.001 (0.010)	0.001 (0.002)	-0.000 (0.003)	0.005 (0.009)	0.002 (0.001)
ARBL Arable	0.002 (0.007)	-0.014 (0.027)	0.008 (0.004)	-0.017 (0.012)	0.036 (0.040)	-0.012 (0.006)
BASG Chalk grassland	0.044 (0.074)	0.021 (0.275)	-0.055 (0.043)	-0.019 (0.044)	-0.075 (0.149)	0.020 (0.023)
BATH Bare artificial	0.006 (0.004)	-0.012 (0.015)	-0.002 (0.002)	**0.010*** **(0.005)**	0.018 (0.016)	0.003 (0.002)
BOGG Bogg	-0.053 (0.228)	-0.240 (1.095)	-0.234 (0.168)	0.132 (0.420)	-0.399 (1.435)	-0.209 (0.233)
BRAK Bracken	0.081 (0.082)	0.369 (0.324)	-0.030 (0.051)	-0.009 (0.066)	0.161 (0.226)	-0.016 (0.037)
BSAR Bare ground	-0.002 (0.024)	-0.029 (0.066)	-0.003 (0.010)	0.006 (0.019)	-0.035 (0.064)	0.004 (0.010)
CONW Conifer woodland	-0.061 (0.112)	-0.335 (0.332)	0.035 (0.051)	**-0.214*** **(0.098)**	0.033 (0.336)	0.049 (0.052)
DTWF Ditch	**1.816***** **(0.471)**	-2.371 (1.641)	0.133 (0.248)	-0.964 (0.621)	-2.294 (2.123)	0.029 (0.321)
FNCR Carr	-3.067 (2.830)	1.604 (1.183)	**0.434*** **(0.183)**	0.566 (0.384)	-0.025 (1.012)	-0.033 (0.151)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
HINA Not available	-0.017 (0.027)	0.072 (0.095)	-0.006 (0.015)	-0.006 (0.006)	0.031 (0.022)	0.000 (0.003)
HTHL Heath	-0.001 (0.103)	-0.086 (0.480)	-0.113 (0.074)	-0.008 (0.087)	-0.449 (0.299)	0.054 (0.048)
IMSS Intertidal	**-0.063* (0.032)**	-0.079 (0.108)	-0.005 (0.016)	0.016 (0.025)	0.029 (0.086)	0.016 (0.013)
IRAG Imp-agri grassland	0.009 (0.012)	-0.004 (0.042)	0.011 (0.007)	0.009 (0.009)	**-0.065* (0.031)**	-0.001 (0.005)
NHRG Herb-rich grassland	0.031 (0.024)	-0.032 (0.083)	0.001 (0.013)	**0.040* (0.020)**	**-0.205** (0.075)**	**0.021* (0.010)**
NNBW Non-native woodland	**-0.044* (0.018)**	-0.027 (0.061)	0.003 (0.010)	-0.011 (0.017)	0.010 (0.058)	0.016 (0.009)
NNHD Non-native hedge	-0.115 (0.147)	0.051 (0.536)	0.132 (0.084)	0.061 (0.139)	0.727 (0.446)	0.088 (0.068)
NSIG Semi-impr grassland	0.002 (0.005)	-0.014 (0.020)	-0.000 (0.003)	0.008 (0.006)	-0.024 (0.019)	-0.002 (0.003)
NTSV Not surveyed	-0.006 (0.006)	0.002 (0.019)	0.002 (0.003)	-0.004 (0.009)	0.022 (0.030)	-0.009 (0.005)
NVBW Native woodland	-0.001 (0.006)	0.021 (0.023)	0.000 (0.004)	-0.002 (0.007)	-0.004 (0.023)	0.002 (0.004)
NVHD Native hedge	-0.043 (0.085)	-0.231 (0.285)	-0.009 (0.045)	-0.037 (0.059)	-0.071 (0.202)	0.041 (0.030)
NWAS Woodland & scrub	-0.105 (0.140)	**1.325* (0.655)**	0.011 (0.117)	0.000 (.)	0.000 (.)	0.000 (.)
ORCH Orchard	0.332 (0.188)	-0.772 (0.797)	**0.296* (0.120)**	0.128 (0.171)	-0.312 (0.591)	0.060 (0.093)
OTHR Other	0.026 (0.039)	0.070 (0.163)	0.021 (0.025)	**0.054* (0.025)**	-0.143 (0.084)	0.018 (0.013)
PLSH	0.012	-0.186	0.007	0.018	0.170	0.004

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Shrubbery	(0.037)	(0.135)	(0.021)	(0.029)	(0.099)	(0.015)
RDEP Ruderal	-0.005 (0.017)	-0.033 (0.055)	0.000 (0.009)	0.001 (0.019)	0.040 (0.066)	0.015 (0.009)
RDSW Reed	0.153 (0.106)	-0.087 (0.269)	-0.051 (0.042)	0.166 (0.115)	-0.620 (0.380)	-0.042 (0.057)
RGHL Roughland	-0.005 (0.014)	0.034 (0.040)	0.008 (0.007)	-0.009 (0.014)	0.076 (0.049)	-0.014 (0.008)
RWRS River	-0.014 (0.011)	-0.053 (0.041)	0.003 (0.006)	0.004 (0.006)	0.019 (0.020)	0.004 (0.003)
SCRB Scrub	0.027 (0.019)	-0.023 (0.069)	0.018 (0.011)	0.026 (0.018)	-0.036 (0.061)	0.018 (0.009)
SCTR Scat trees	0.004 (0.012)	0.041 (0.041)	-0.001 (0.006)	0.003 (0.011)	-0.004 (0.036)	0.007 (0.005)
STMS Saltmarsh	-0.026 (0.436)	1.795 (2.025)	-0.129 (0.363)	0.369 (1.232)	2.704 (4.210)	-0.198 (0.669)
STWC Still water	-0.007 (0.020)	0.013 (0.075)	0.015 (0.011)	**0.024***** **(0.007)**	**-0.057*** **(0.023)**	-0.002 (0.003)
TLHB Tall herb	-0.022 (0.023)	-0.009 (0.085)	0.010 (0.013)	0.011 (0.027)	-0.172 (0.092)	0.018 (0.014)
TYSW Swamp	0.234 (0.256)	-0.309 (0.800)	-0.150 (0.124)	0.217 (0.246)	1.531 (0.809)	**-0.314**** **(0.111)**
VEGW Vegetated walls	0.002 (0.016)	**-0.190**** **(0.070)**	-0.003 (0.011)	-0.064 (0.143)	0.118 (0.484)	-0.047 (0.076)
WOOD Woodland	-18.310 (69.465)	63.956 (333.748)	-78.888 (51.179)	-0.003 (0.054)	0.106 (0.185)	-0.017 (0.030)
WTMV Wet marginal	-0.156 (0.163)	-0.026 (0.572)	-0.007 (0.090)	-0.077 (0.109)	**0.748*** **(0.370)**	-0.034 (0.055)
Habitat categories						

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Grassland	0.003	-0.002	0.001	0.002	-0.006	0.001
	(0.002)	(0.008)	(0.001)	(0.002)	(0.007)	(0.001)
Maintained	0.002	-0.002	0.002	-0.000	0.004	0.002
	(0.003)	(0.010)	(0.001)	(0.003)	(0.009)	(0.001)
Use	0.005	-0.010	0.002	-0.001	0.007	0.002
	(0.003)	(0.010)	(0.001)	(0.003)	(0.009)	(0.001)
Water	-0.011	-0.036	0.005	**0.012****	-0.012	0.001
	(0.009)	(0.035)	(0.005)	**(0.004)**	(0.015)	(0.002)
Wet	-0.036	-0.078	-0.013	0.016	0.038	0.005
	(0.028)	(0.092)	(0.014)	(0.022)	(0.074)	(0.011)
Wild	0.003	0.005	0.005	0.003	0.030	0.002
	(0.008)	(0.025)	(0.004)	(0.008)	(0.028)	(0.004)
Woodland	-0.004	0.019	0.000	-0.002	-0.001	0.004
	(0.005)	(0.019)	(0.003)	(0.005)	(0.017)	(0.003)
Habitat diversity						
Richness	0.009	-0.024	0.002	0.003	-0.015	0.004
	(0.005)	(0.019)	(0.003)	(0.005)	(0.016)	(0.002)
Shannon’s Index	0.038	-0.155	0.034	0.061	-0.081	0.046
	(0.052)	(0.187)	(0.029)	(0.049)	(0.168)	(0.025)
Simpson’s Index	0.060	-0.371	0.069	0.154	-0.060	0.099
	(0.116)	(0.412)	(0.064)	(0.109)	(0.371)	(0.056)
Biodiversity						
Butterfly species richness	-0.004	0.007	**0.004***	0.000	-0.016	-0.001
	(0.004)	(0.014)	**(0.002)**	(0.003)	(0.011)	(0.002)
Bird species richness	-0.000	0.003	**0.001***	0.001	-0.000	-0.001
	(0.001)	(0.003)	**(0.001)**	(0.001)	(0.003)	(0.000)
Plant species richness	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Total species richness	-0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	0.000 (0.000)
NDVI						
NDVI mean	-0.129 (0.331)	-0.552 (1.160)	0.191 (0.181)	-0.031 (0.289)	-1.023 (0.989)	**0.324*** **(0.147)**
NDVI stdev	0.142 (0.974)	-5.424 (3.421)	0.446 (0.532)	-0.614 (0.874)	-0.168 (2.984)	**1.014*** **(0.440)**
Spatial control variables						
Income deprivation	-0.754 (0.714)	**-6.111*** **(2.609)**	**-1.456***** **(0.408)**	-0.408 (0.612)	-1.706 (2.077)	-0.244 (0.303)
Employment deprivation	2.301 (1.330)	9.149 (4.794)	**2.389**** **(0.747)**	0.771 (1.255)	2.500 (4.256)	0.422 (0.622)
Education deprivation	-0.005 (0.004)	**0.028*** **(0.014)**	0.002 (0.002)	-0.001 (0.004)	0.008 (0.013)	-0.002 (0.002)
Crime deprivation	-0.074 (0.060)	0.040 (0.202)	0.018 (0.032)	0.073 (0.051)	0.318 (0.174)	0.039 (0.026)
NO_2	-0.000 (0.006)	0.034 (0.019)	-0.001 (0.003)	0.002 (0.005)	0.007 (0.016)	-0.000 (0.002)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.354**** **(0.123)**	0.445 (0.440)	**-0.208**** **(0.069)**	-0.065 (0.101)	0.204 (0.340)	-0.091 (0.051)
26-35	**-0.308***** **(0.092)**	**0.655*** **(0.327)**	-0.091 (0.051)	-0.030 (0.073)	0.230 (0.248)	-0.029 (0.037)
36-45	**-0.202***** **(0.061)**	**0.467*** **(0.215)**	-0.003 (0.033)	-0.039 (0.048)	0.013 (0.162)	-0.008 (0.024)
56-65	**0.152*** **(0.063)**	**-0.988***** **(0.222)**	0.035 (0.035)	0.110 (0.057)	**-0.544**** **(0.194)**	-0.034 (0.029)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
66-75	0.172	**-0.862***	-0.012	**0.222***	**-0.872****	0.008
	(0.107)	**(0.379)**	(0.059)	**(0.092)**	**(0.312)**	(0.047)
75+	0.039	-0.500	-0.101	0.237	-0.623	-0.056
	(0.147)	(0.528)	(0.082)	(0.132)	(0.448)	(0.067)
University-level qualification	**-0.231***	0.150	-0.006	-0.104	0.138	-0.026
	(0.110)	(0.339)	(0.053)	(0.072)	(0.246)	(0.037)
In a relationship	**0.254*****	**-0.490****	0.034	0.078	-0.055	-0.021
	(0.052)	**(0.181)**	(0.028)	(0.048)	(0.163)	(0.024)
Living with children	-0.060	-0.136	-0.000	-0.032	0.045	-0.019
	(0.051)	(0.178)	(0.028)	(0.043)	(0.147)	(0.022)
Annual household income	-0.013	0.016	**-0.033****	0.020	**-0.144***	-0.001
	(0.019)	(0.074)	**(0.012)**	(0.017)	**(0.057)**	(0.008)
Health condition	**-0.399*****	**1.977*****	**-0.579*****	**-0.149*****	**0.873*****	**-0.331*****
	(0.044)	**(0.152)**	**(0.023)**	**(0.025)**	**(0.085)**	**(0.013)**
Employment status (reference: employed)						
Unemployed	**-0.307*****	**0.992*****	**-0.125****	**-0.277*****	**1.617*****	**-0.067****
	(0.071)	**(0.248)**	**(0.039)**	**(0.046)**	**(0.156)**	**(0.023)**
Retired	0.101	**-0.569***	-0.010	**0.130***	-0.391	0.052
	(0.075)	**(0.273)**	(0.043)	**(0.065)**	(0.222)	(0.033)
Caring for family	0.074	0.168	-0.070	**0.047**	0.314	-0.012
	(0.071)	(0.254)	(0.040)	(0.051)	(0.173)	(0.025)
In training	-0.033	-0.200	**-0.108***	0.083	0.277	0.009
	(0.083)	(0.284)	**(0.045)**	(0.055)	(0.187)	(0.028)
Other	-0.367*	0.190	-0.122	-0.008	0.392	0.008
	(0.149)	(0.626)	(0.099)	(0.104)	(0.355)	(0.053)
House type (reference category: detached)						

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Semi-detached	**-0.163**[*]	-0.100	0.000	-	**-**	-
	(0.076)	(0.277)	(0.043)			
Terraced	-0.103	-0.187	-0.007	-	-	-
	(0.082)	(0.294)	(0.046)			
Flat	-0.104	0.038	-0.025	-	-	-
	(0.088)	(0.316)	(0.049)			
Other	**-0.332**[*]	0.510	-0.026	-	**-**	-
	(0.131)	(0.479)	(0.075)			
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.087	**0.604**[**]	-0.038	0.060	-0.143	-0.026
	(0.064)	**(0.224)**	(0.035)	(0.043)	(0.147)	(0.021)
3 $\geq$ rooms per person	0.020	**-0.450**[*]	0.052	-0.009	0.147	**-0.053**[*]
	(0.053)	**(0.185)**	(0.029)	(0.049)	(0.167)	**(0.025)**
Commuting time (reference category: None)						
$\leq$ 15 mins	0.023	-0.204	-0.002	-0.010	**-0.291**[*]	0.038
	(0.058)	(0.210)	(0.033)	(0.043)	**(0.146)**	(0.022)
16-30 mins	0.080	**-0.450**[*]	-0.006	-0.029	-0.064	0.024
	(0.057)	**(0.208)**	(0.033)	(0.040)	(0.134)	(0.020)
31-50 mins	0.085	-0.402	-0.001	-0.026	-0.064	0.013
	(0.061)	(0.223)	(0.035)	(0.041)	(0.140)	(0.021)
$\geq$ 50 mins	0.073	-0.073	-0.041	-0.020	0.034	0.006
	(0.061)	(0.224)	(0.035)	(0.041)	(0.139)	(0.021)
Other						
Wave	**-0.016**[***]	**0.069**[***]	**-0.020**[***]	0.008	0.005	**-0.025**[***]
	(0.005)	**(0.017)**	**(0.003)**	(0.005)	(0.016)	**(0.002)**
Constant	**5.600**[***]	**9.373**[***]	**4.461**[***]	**4.680**[***]	**11.257**[***]	**4.188**[***]

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
	(0.277)	**(0.940)**	**(0.147)**	**(0.230)**	**(0.783)**	**(0.116)**
R_2	0.04	0.03	0.12	0.05	0.07	0.23
Observations	8,469	13,622	13,077	34,061	34,947	41,807
Individuals	1,589	2,139	2,162	10,414	10,764	12,053
Mean obs per individual	5.3	6.3	6	3.3	3.2	3.4

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

TableS5.3. Distance decay regression results, showing unstandardised coefficients (full results from Distance only model).

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Distance only	0.921 (2.576)	5.639 (8.003)	-0.371 (1.236)	-0.031 (0.051)	0.189 (0.176)	0.011 (0.027)
Area	0.238 (0.664)	1.108 (2.111)	-0.159 (0.326)	-0.007 (0.013)	0.046 (0.043)	0.003 (0.007)
Habitat types						
ACDG Acid grassland	-0.001 (0.001)	-0.002 (0.004)	-0.000 (0.001)	0.002 (0.001)	-0.002 (0.004)	0.000 (0.000)
ALTA Allotments	0.000 (0.001)	-0.003 (0.002)	0.000 (0.000)	0.001 (0.001)	-0.000 (0.001)	**-0.001*** **(0.000)**
AMNG Amenity grassland	-0.000 (0.000)	0.001 (0.001)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
ARBL Arable	0.000 (0.001)	0.005 (0.003)	**-0.001*** **(0.000)**	**-0.001*** **(0.001)**	0.002 (0.002)	-0.000 (0.000)
BASG Chalk grassland	0.002 (0.005)	0.003 (0.006)	0.001 (0.001)	0.002 (0.002)	0.000 (0.007)	0.001 (0.001)
BATH Bare artificial	**-0.002*** **(0.001)**	0.001 (0.001)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
BOGG Bogg	-5.184 (5.171)	-1.367 (1.544)	-0.158 (0.237)	3.084 (7.099)	-6.210 (24.252)	1.750 (3.686)
BRAK Bracken	0.035 (0.044)	0.240 (0.153)	-0.024 (0.023)	-0.052 (0.047)	0.136 (0.160)	-0.026 (0.024)
BSAR Bare ground	0.000 (0.001)	**0.010*** **(0.004)**	**-0.002**** **(0.001)**	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
CONW Conifer woodland	-0.006 (0.015)	0.094 (0.058)	-0.007 (0.009)	**0.006**** **(0.002)**	**-0.016*** **(0.007)**	0.000 (0.001)
DTWF Ditch	-0.002 (0.008)	-0.011 (0.040)	-0.002 (0.006)	**-0.004***** **(0.001)**	-0.003 (0.004)	0.000 (0.001)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
FNCR Carr	0.001 (0.003)	**0.031*** **(0.016)**	**-0.008***** **(0.002)**	-0.028 (0.039)	**0.349**** **(0.133)**	-0.007 (0.016)
HINA Not available	0.007 (0.076)	-0.146 (0.323)	-0.011 (0.050)	-0.010 (0.037)	0.049 (0.126)	0.013 (0.020)
HTHL Heath	-0.828 (0.706)	0.502 (1.536)	0.201 (0.238)	0.000 (0.015)	0.049 (0.052)	-0.001 (0.008)
IMSS Intertidal	-0.001 (0.012)	0.007 (0.058)	-0.003 (0.009)	-0.001 (0.003)	-0.006 (0.012)	0.002 (0.002)
IRAG Imp-agri grassland	-0.001 (0.001)	0.004 (0.002)	0.000 (0.000)	**-0.001*** **(0.000)**	0.002 (0.001)	-0.000 (0.000)
NHRG Herb-rich grassland	0.000 (0.001)	**0.012*** **(0.005)**	**-0.002**** **(0.001)**	-0.000 (0.001)	0.001 (0.003)	-0.000 (0.000)
NNBW Non-native woodland	-0.000 (0.000)	**0.003*** **(0.001)**	**-0.001**** **(0.000)**	-0.001 (0.000)	0.003 (0.002)	0.000 (0.000)
NNHD Non-native hedge	-0.001 (0.028)	-0.034 (0.109)	-0.024 (0.017)	0.013 (0.008)	0.046 (0.026)	-0.004 (0.004)
NSIG Semi-impr grassland	0.000 (0.001)	-0.002 (0.003)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
NTSV Not surveyed	-0.005 (0.003)	0.007 (0.008)	0.000 (0.001)	0.000 (0.000)	-0.001 (0.000)	**-0.000*** **(0.000)**
NVBW Native woodland	0.000 (0.000)	**0.001*** **(0.000)**	**-0.000***** **(0.000)**	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
NVHD Native hedge	0.005 (0.006)	-0.007 (0.025)	0.003 (0.004)	-0.001 (0.001)	0.004 (0.005)	-0.001 (0.001)
NWAS Woodland & scrub	3.357 (10.977)	0.406 (0.352)	-0.034 (0.054)	**-0.031*** **(0.014)**	0.043 (0.047)	0.002 (0.008)
ORCH Orchard	-0.004 (0.003)	0.019 (0.016)	0.001 (0.003)	-0.022 (0.071)	0.105 (0.242)	0.017 (0.033)
OTHR	**0.116***	0.006	-0.000	-0.000	0.000	-0.000

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Other	**(0.059)**	(0.004)	(0.001)	(0.000)	(0.000)	(0.000)
PLSH Shrubbery	-0.005 (0.007)	-0.015 (0.016)	0.000 (0.002)	0.001 (0.002)	**0.012* (0.005)**	**-0.002*** (0.001)**
RDEP Ruderal	-0.003 (0.003)	0.014 (0.009)	**-0.004** (0.001)**	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
RDSW Reed	-0.007 (0.054)	-0.340 (0.237)	-0.058 (0.036)	-0.002 (0.004)	-0.010 (0.013)	0.002 (0.002)
RGHL Roughland	0.001 (0.001)	**0.011* (0.005)**	-0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
RWRS River	-0.000 (0.003)	0.003 (0.012)	0.000 (0.002)	**-0.001*** (0.000)**	-0.000 (0.001)	-0.000 (0.000)
SCRB Scrub	0.000 (0.000)	**0.002* (0.001)**	**-0.000** (0.000)**	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
SCTR Scat trees	0.001 (0.001)	0.000 (0.003)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
STMS Saltmarsh	0.954 (2.286)	0.393 (0.681)	**-0.210* (0.102)**	**-0.111* (0.049)**	0.155 (0.169)	0.006 (0.027)
STWC Still water	0.001 (0.002)	0.000 (0.007)	-0.002 (0.001)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
TLHB Tall herb	0.003 (0.002)	0.002 (0.008)	-0.002 (0.001)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
TYSW Swamp	-0.021 (0.023)	-0.012 (0.103)	-0.007 (0.016)	-0.005 (0.006)	0.008 (0.021)	-0.003 (0.002)
VEGW Vegetated walls	0.044 (0.052)	-0.225 (0.190)	-0.055 (0.029)	-0.010 (0.016)	0.092 (0.051)	-0.013 (0.008)
WOOD Woodland	-0.005 (0.120)	-0.247 (0.559)	0.071 (0.089)	-0.008 (0.015)	0.009 (0.050)	-0.012 (0.008)
WTMV Wet marginal	-0.041 (0.042)	0.152 (0.163)	-0.037 (0.024)	-0.001 (0.001)	-0.002 (0.002)	0.000 (0.000)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Habitat categories						
Grassland	-0.000	0.001	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maintained	-0.000	0.001	-0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Use	-0.000	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Water	0.001	0.001	-0.001	-0.000	0.000	-0.000
	(0.002)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)
Wet	-0.003	-0.005	-0.004	**-0.001***	-0.001	0.000
	(0.006)	(0.028)	(0.004)	**(0.000)**	(0.002)	(0.000)
Wild	0.000	**0.002***	**-0.000****	-0.000	0.000	-0.000
	(0.000)	**(0.001)**	**(0.000)**	(0.000)	(0.000)	(0.000)
Woodland	0.000	**0.001***	**0.000*****	-0.000	-0.000	-0.000
	(0.000)	**(0.000)**	**(0.000)**	(0.000)	(0.000)	(0.000)
Habitat diversity						
Habitat richness	0.720	-0.520	-0.378	-0.021	0.203	0.011
	(1.368)	(4.910)	(0.764)	(0.045)	(0.154)	(0.024)
Habitat Shannon’s	0.400	-41.261	-4.825	-0.483	1.681	0.040
	(12.433)	(39.082)	(6.043)	(0.344)	(1.177)	(0.184)
Habitat Simpson’s	-1.856	-77.469	-9.147	-0.932	2.640	0.038
	(24.497)	(76.000)	(11.733)	(0.590)	(2.016)	(0.318)
Biodiversity						
Butterfly richness	2.832	12.789	-2.884	-0.099	0.594	-0.008
	(3.212)	(11.887)	(1.828)	(0.200)	(0.680)	(0.106)
Bird richness	0.775	-0.047	-0.808	-0.036	0.057	-0.037
	(1.431)	(5.677)	(0.906)	(0.059)	(0.201)	(0.032)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Plant richness	-0.061	-0.173	0.066	-0.014	0.043	0.001
	(0.338)	(1.063)	(0.165)	(0.012)	(0.041)	(0.006)
Total species richness	0.004	-0.105	0.012	-0.013	0.038	-0.000
	(0.270)	(0.896)	(0.140)	(0.011)	(0.038)	(0.006)
NDVI						
NDVI mean	2.771	7.585	-1.387	-0.094	0.497	0.028
	(4.439)	(14.635)	(2.265)	(0.134)	(0.457)	(0.070)
NDVI std	18.456	8.546	-18.192	-0.168	1.768	0.102
	(31.669)	(103.205)	(15.897)	(0.469)	(1.602)	(0.248)
Spatial control variables						
Income deprivation	-0.803	**-6.180***	**-1.460*****	-0.418	-1.716	-0.246
	(0.713)	**(2.614)**	**(0.409)**	(0.612)	(2.077)	(0.303)
Employment deprivation	2.370	9.401	**2.372****	0.732	2.496	0.382
	(1.332)	(4.807)	**(0.749)**	(1.254)	(4.253)	(0.621)
Education deprivation	-0.005	0.025	0.002	-0.001	0.008	-0.002
	(0.004)	(0.014)	(0.002)	(0.004)	(0.013)	(0.002)
Crime deprivation	-0.070	0.045	0.018	0.074	0.320	0.041
	(0.060)	(0.203)	(0.032)	(0.051)	(0.174)	(0.026)
NO_2	-0.001	0.036	-0.002	0.002	0.006	-0.001
	(0.006)	(0.019)	(0.003)	(0.005)	(0.016)	(0.002)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.357****	0.455	**-0.210****	-0.065	0.203	-0.091
	(0.123)	(0.440)	**(0.069)**	(0.101)	(0.340)	(0.051)
26-35	**-0.310*****	**0.662***	-0.093	-0.029	0.228	-0.028
	(0.092)	**(0.327)**	(0.051)	(0.073)	(0.248)	(0.037)
36-45	**-0.202*****	**0.476***	-0.004	-0.039	0.011	-0.008
	(0.061)	**(0.215)**	(0.033)	(0.048)	(0.162)	(0.024)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
56-65	**0.156***	**-1.001*** **	0.037	0.110	**-0.544** **	-0.035
	(0.062)	**(0.222)**	(0.035)	(0.057)	**(0.194)**	(0.029)
66-75	0.176	**-0.869***	-0.010	**0.221***	**-0.871** **	0.008
	(0.107)	**(0.379)**	(0.059)	**(0.092)**	**(0.312)**	(0.047)
75+	0.042	-0.501	-0.101	0.237	-0.621	-0.056
	(0.147)	(0.528)	(0.082)	(0.132)	(0.448)	(0.067)
University-level qualification	**-0.230***	0.147	-0.005	-0.104	0.139	-0.026
	(0.110)	(0.339)	(0.053)	(0.072)	(0.246)	(0.037)
In a relationship	**0.254*** **	**-0.488** **	0.033	0.078	-0.054	-0.020
	(0.052)	**(0.181)**	(0.028)	(0.048)	(0.163)	(0.024)
Living with children	-0.060	-0.139	0.000	-0.032	0.050	-0.019
	(0.051)	(0.178)	(0.028)	(0.043)	(0.147)	(0.022)
Annual household income	-0.013	0.017	**-0.033** **	0.020	**-0.144***	-0.001
	(0.019)	(0.074)	**(0.012)**	(0.017)	**(0.057)**	(0.008)
Health condition	**-0.399*** **	**1.975*** **	**-0.579*** **	**-0.149*** **	**0.873*** **	**-0.331*** **
	(0.044)	**(0.152)**	**(0.023)**	**(0.025)**	**(0.085)**	**(0.013)**
Employment status (reference: employed)						
Unemployed	**-0.307*** **	**0.992*** **	**-0.125** **	**-0.277*** **	**1.618*** **	**-0.066** **
	(0.071)	**(0.248)**	**(0.039)**	**(0.046)**	**(0.156)**	**(0.023)**
Retired	0.101	**-0.567***	-0.011	**0.130***	-0.390	0.051
	(0.075)	**(0.273)**	(0.043)	**(0.065)**	(0.222)	(0.033)
Caring for family	0.074	0.172	-0.070	0.047	0.315	-0.012
	(0.071)	(0.254)	(0.040)	(0.051)	(0.173)	(0.025)
In training	-0.031	-0.206	**-0.106***	0.083	0.279	0.009
	(0.083)	(0.284)	**(0.045)**	(0.055)	(0.187)	(0.028)
Other	**-0.367***	0.180	-0.119	-0.008	0.394	0.008
	(0.149)	(0.626)	(0.099)	(0.104)	(0.355)	(0.053)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
House type (reference category: detached)						
Semi-detached	**-0.166*** **(0.076)**	-0.090 (0.277)	-0.002 (0.043)	-	-	-
Terraced	-0.105 (0.082)	-0.182 (0.294)	-0.007 (0.046)	-	-	-
Flat	-0.106 (0.088)	0.029 (0.316)	-0.024 (0.049)	-	-	-
Other	**-0.329*** **(0.131)**	0.489 (0.479)	-0.024 (0.075)	-	-	-
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.087 (0.064)	**0.601**** **(0.224)**	-0.038 (0.035)	0.059 (0.043)	-0.146 (0.147)	-0.027 (0.021)
3 $\geq$ rooms per person	0.020 (0.053)	**-0.440*** **(0.185)**	0.050 (0.029)	-0.010 (0.049)	0.150 (0.167)	**-0.053*** **(0.025)**
Commuting time (reference category: None)						
$\leq$ 15 mins	0.023 (0.058)	-0.203 (0.210)	-0.002 (0.033)	-0.010 (0.043)	**-0.289*** **(0.146)**	0.038 (0.022)
16-30 mins	0.079 (0.057)	**-0.450*** **(0.208)**	-0.006 (0.033)	-0.029 (0.040)	-0.063 (0.134)	0.024 (0.020)
31-50 mins	0.084 (0.061)	-0.405 (0.223)	-0.001 (0.035)	-0.026 (0.041)	-0.063 (0.140)	0.013 (0.021)
$\geq$ 50 mins	0.074 (0.061)	-0.075 (0.224)	-0.040 (0.035)	-0.020 (0.041)	0.035 (0.139)	0.006 (0.021)
Other						
Wave	**-0.016****	**0.069*****	**-0.020*****	0.008	0.004	**-0.025*****

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
	(0.005)	**(0.016)**	**(0.003)**	(0.005)	(0.016)	**(0.002)**
R^2	0.04	0.03	0.13	0.05	0.07	0.24
Observations	8,469	13,622	13,077	34,061	34,947	41,087
Individuals	1,589	2,139	2,162	10,414	10,764	12,053
Mean obs per person	5.3	6.4	6	3.3	3.2	3.4

Standard errors in parentheses

*p<0.001, **p<0.01, ***p<0.05

Table S5.4. LSOA-level regression results, showing standardised coefficients (full results from All OSS model only).

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
All OSS	0.023 (0.001)	-0.015 (0.005)	0.021 (0.001)	0.010 (0.001)	0.005 (0.004)	0.016 (0.001)
Habitat types						
ACDG Acid grassland	0.016 (0.010)	0.004 (0.035)	-0.014 (0.005)	-0.008 (0.016)	-0.001 (0.054)	0.008 (0.008)
ALTA Allotments	**0.100**** **(0.016)**	**-0.079*** **(0.059)**	0.003 (0.009)	-0.010 (0.013)	0.001 (0.043)	0.008 (0.007)
AMNG Amenity grassland	0.021 (0.003)	-0.001 (0.010)	0.013 (0.002)	-0.002 (0.003)	0.008 (0.009)	0.016 (0.001)
ARBL Arable	0.004 (0.007)	-0.007 (0.027)	0.023 (0.004)	-0.027 (0.012)	0.016 (0.040)	-0.027 (0.006)
BASG Chalk grassland	0.010 (0.074)	0.001 (0.275)	-0.016 (0.043)	-0.005 (0.044)	-0.006 (0.149)	0.008 (0.023)
BATH Bare artificial	0.031 (0.004)	-0.014 (0.015)	-0.017 (0.002)	**0.033*** **(0.005)**	0.015 (0.016)	0.013 (0.002)
BOGG Bogg	-0.003 (0.228)	-0.003 (1.095)	-0.015 (0.168)	0.002 (0.420)	-0.001 (1.435)	-0.003 (0.233)
BRAK Bracken	-0.003 (0.228)	-0.003 (1.095)	-0.015 (0.168)	-0.002 (0.066)	0.010 (0.226)	-0.005 (0.037)
BSAR Bare ground	-0.002 (0.024)	-0.006 (0.066)	-0.004 (0.010)	0.004 (0.019)	-0.007 (0.064)	0.004 (0.010)
CONW Conifer woodland	-0.009 (0.112)	-0.012 (0.332)	0.007 (0.051)	**-0.035*** **(0.098)**	0.001 (0.336)	0.011 (0.052)
DTWF Ditch	**0.090***** **(0.471)**	-0.025 (1.641)	0.008 (0.248)	-0.040 (0.621)	-0.025 (2.123)	0.002 (0.321)
FNCR Carr	-0.178 (2.830)	0.019 (1.183)	**0.029*** **(0.183)**	0.025 (0.384)	-0.000 (1.012)	-0.002 (0.151)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
HINA Not available	-0.011 (0.027)	0.009 (0.095)	-0.005 (0.015)	-0.016 (0.006)	0.023 (0.022)	0.000 (0.003)
HTHL Heath	-0.000 (0.103)	-0.002 (0.480)	-0.012 (0.074)	-0.002 (0.087)	-0.024 (0.299)	0.016 (0.048)
IMSS Intertidal	**-0.039*** **(0.032)**	-0.009 (0.108)	-0.004 (0.016)	0.008 (0.025)	0.004 (0.086)	0.012 (0.013)
IRAG Imp-agri grassland	0.021 (0.012)	-0.002 (0.042)	0.038 (0.007)	0.014 (0.009)	**-0.027*** **(0.031)**	-0.003 (0.005)
NHRG Herb-rich grassland	0.034 (0.024)	-0.008 (0.083)	0.002 (0.013)	**0.030*** **(0.020)**	**-0.042**** **(0.075)**	**0.022*** **(0.010)**
NNBW Non-native woodland	**-0.045*** **(0.018)**	-0.007 (0.061)	0.004 (0.010)	-0.011 (0.017)	0.003 (0.058)	0.020 (0.009)
NNHD Non-native hedge	-0.014 (0.147)	0.001 (0.536)	0.021 (0.084)	0.009 (0.139)	0.030 (0.446)	0.018 (0.068)
NSIG Semi-impr grassland	0.010 (0.005)	-0.017 (0.020)	-0.002 (0.003)	0.025 (0.006)	-0.020 (0.019)	-0.009 (0.003)
NTSV Not surveyed	-0.020 (0.006)	0.001 (0.019)	0.007 (0.003)	-0.006 (0.009)	0.008 (0.030)	-0.016 (0.005)
NVBW Native woodland	-0.004 (0.006)	0.013 (0.023)	0.001 (0.004)	-0.007 (0.007)	-0.003 (0.023)	0.008 (0.004)
NVHD Native hedge	-0.014 (0.085)	-0.018 (0.285)	-0.004 (0.045)	-0.011 (0.059)	-0.006 (0.202)	0.016 (0.030)
NWAS Woodland & scrub	-0.007 (0.140)	**0.016*** **(0.655)**	0.001 (0.117)	0.000 (.)	0.000 (.)	0.000 (.)
ORCH Orchard	0.031 (0.188)	-0.017 (0.797)	**0.039*** **(0.120)**	0.010 (0.171)	-0.006 (0.591)	0.006 (0.093)
OTHR Other	0.010 (0.039)	0.005 (0.163)	0.010 (0.025)	**0.026*** **(0.025)**	-0.019 (0.084)	0.012 (0.013)
PLSH	0.005	-0.018	0.004	0.009	0.024	0.003

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Shrubbery	(0.037)	(0.135)	(0.021)	(0.029)	(0.099)	(0.015)
RDEP Ruderal	-0.006 (0.017)	-0.008 (0.055)	0.001 (0.009)	0.001 (0.019)	0.008 (0.066)	0.015 (0.009)
RDSW Reed	0.048 (0.106)	-0.006 (0.269)	-0.021 (0.042)	0.038 (0.115)	-0.037 (0.380)	-0.013 (0.057)
RGHL Roughland	-0.008 (0.014)	0.013 (0.040)	0.017 (0.007)	-0.009 (0.014)	0.020 (0.049)	-0.019 (0.008)
RWRS River	-0.023 (0.011)	-0.018 (0.041)	0.005 (0.006)	0.009 (0.006)	0.012 (0.020)	0.013 (0.003)
SCRB Scrub	0.032 (0.019)	-0.006 (0.069)	0.029 (0.011)	0.024 (0.018)	-0.009 (0.061)	0.023 (0.009)
SCTR Scat trees	0.006 (0.012)	0.016 (0.041)	-0.002 (0.006)	0.005 (0.011)	-0.002 (0.036)	0.014 (0.005)
STMS Saltmarsh	-0.001 (0.436)	0.007 (2.025)	-0.003 (0.363)	0.013 (1.232)	0.025 (4.210)	-0.010 (0.669)
STWC Still water	-0.008 (0.020)	0.003 (0.075)	0.021 (0.011)	**0.056***** **(0.007)**	**-0.035*** **(0.023)**	-0.006 (0.003)
TLHB Tall herb	-0.019 (0.023)	-0.002 (0.085)	0.013 (0.013)	0.009 (0.027)	-0.035 (0.092)	0.018 (0.014)
TYSW Swamp	0.039 (0.256)	-0.012 (0.800)	-0.033 (0.124)	0.048 (0.246)	0.088 (0.809)	**-0.088**** **(0.111)**
VEGW Vegetated walls	0.001 (0.016)	**-0.026**** **(0.070)**	-0.003 (0.011)	-0.023 (0.143)	0.011 (0.484)	-0.021 (0.076)
WOOD Woodland	-0.002 (69.465)	0.002 (333.748)	-0.011 (51.179)	-0.001 (0.054)	0.008 (0.185)	-0.007 (0.030)
WTMV Wet marginal	-0.027 (0.163)	-0.001 (0.572)	-0.002 (0.090)	-0.011 (0.109)	**0.028*** **(0.370)**	-0.006 (0.055)
Habitat categories						

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Grassland	0.032	-0.006	0.011	0.013	-0.012	0.013
	(0.002)	(0.008)	(0.001)	(0.002)	(0.007)	(0.001)
Maintained	0.017	-0.003	0.015	-0.001	0.007	0.017
	(0.003)	(0.010)	(0.001)	(0.003)	(0.009)	(0.001)
Use	0.035	-0.018	0.023	-0.009	0.010	0.013
	(0.003)	(0.010)	(0.001)	(0.003)	(0.009)	(0.001)
Water	-0.024	-0.015	0.013	**0.041****	-0.011	0.007
	(0.009)	(0.035)	(0.005)	**(0.004)**	(0.015)	(0.002)
Wet	-0.030	-0.014	-0.014	0.012	0.008	0.005
	(0.028)	(0.092)	(0.014)	(0.022)	(0.074)	(0.011)
Wild	0.007	0.003	0.017	0.005	0.015	0.005
	(0.008)	(0.025)	(0.004)	(0.008)	(0.028)	(0.004)
Woodland	-0.014	0.016	0.001	-0.008	-0.001	0.019
	(0.005)	(0.019)	(0.003)	(0.005)	(0.017)	(0.003)
Habitat diversity						
Richness	0.037	-0.023	0.014	0.012	-0.014	0.017
	(0.005)	(0.019)	(0.003)	(0.005)	(0.016)	(0.002)
Shannon’s Index	0.017	-0.016	0.020	0.021	-0.007	0.021
	(0.052)	(0.187)	(0.029)	(0.049)	(0.168)	(0.025)
Simpson’s Index	0.012	-0.017	0.018	0.024	-0.002	0.021
	(0.116)	(0.412)	(0.064)	(0.109)	(0.371)	(0.056)
Biodiversity						
Butterfly species richness	-0.028	0.012	**0.042***	0.001	-0.023	-0.008
	(0.004)	(0.014)	**(0.002)**	(0.003)	(0.011)	(0.002)
Bird species richness	-0.004	0.014	**0.034***	0.011	-0.001	-0.012
	(0.001)	(0.003)	**(0.001)**	(0.001)	(0.003)	(0.000)
Plant species richness	-0.000	-0.000	0.020	-0.005	-0.006	0.010
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Total species richness	-0.003 (0.000)	0.005 (0.001)	0.027 (0.000)	-0.001 (0.000)	-0.006 (0.001)	0.003 (0.000)
NDVI						
NDVI mean	-0.010 (0.331)	-0.010 (1.160)	0.021 (0.181)	-0.002 (0.289)	-0.019 (0.989)	**0.031*** **(0.147)**
NDVI stdev	0.003 (0.974)	-0.029 (3.421)	0.014 (0.532)	-0.011 (0.874)	-0.001 (2.984)	**0.026*** **(0.440)**
Spatial control variables						
Income deprivation	-0.060 (0.714)	**-0.112*** **(2.609)**	**-0.156***** **(0.408)**	-0.033 (0.612)	-0.037 (2.077)	-0.028 (0.303)
Employment deprivation	0.081 (1.330)	0.075 (4.794)	**0.114**** **(0.747)**	0.025 (1.255)	0.022 (4.256)	0.019 (0.622)
Education deprivation	-0.042 (0.004)	**0.054*** **(0.014)**	0.017 (0.002)	-0.008 (0.004)	0.015 (0.013)	-0.018 (0.002)
Crime deprivation	-0.035 (0.060)	0.004 (0.202)	0.011 (0.032)	0.028 (0.051)	0.032 (0.174)	0.020 (0.026)
NO_2	-0.002 (0.006)	0.041 (0.019)	-0.009 (0.003)	0.010 (0.005)	0.008 (0.016)	-0.001 (0.002)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.104**** **(0.123)**	0.031 (0.440)	**-0.085**** **(0.069)**	-0.017 (0.101)	0.014 (0.340)	-0.032 (0.051)
26-35	**-0.099***** **(0.092)**	**0.050*** **(0.327)**	-0.040 (0.051)	-0.008 (0.073)	0.016 (0.248)	-0.010 (0.037)
36-45	**-0.063***** **(0.061)**	**0.033*** **(0.215)**	-0.001 (0.033)	-0.011 (0.048)	0.001 (0.162)	-0.003 (0.024)
56-65	**0.041*** **(0.063)**	**-0.060***** **(0.222)**	0.012 (0.035)	0.023 (0.057)	**-0.031**** **(0.194)**	-0.010 (0.029)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
66-75	0.039	**-0.044***	-0.003	**0.040***	**-0.041****	0.002
	(0.107)	**(0.379)**	(0.059)	**(0.092)**	**(0.312)**	(0.047)
75+	0.008	-0.022	-0.026	0.031	-0.022	-0.010
	(0.147)	(0.528)	(0.082)	(0.132)	(0.448)	(0.067)
University-level qualification	**-0.085***	0.012	-0.003	-0.034	0.012	-0.012
	(0.110)	(0.339)	(0.053)	(0.072)	(0.246)	(0.037)
In a relationship	**0.099*****	**-0.045****	0.018	0.026	-0.005	-0.009
	(0.052)	**(0.181)**	(0.028)	(0.048)	(0.163)	(0.024)
Living with children	-0.020	-0.011	-0.000	-0.010	0.004	-0.008
	(0.051)	(0.178)	(0.028)	(0.043)	(0.147)	(0.022)
Annual household income	-0.008	0.003	**-0.030****	0.009	**-0.018***	-0.001
	(0.019)	(0.074)	**(0.012)**	(0.017)	**(0.057)**	(0.008)
Health condition	**-0.116*****	**0.135*****	**-0.231*****	**-0.043*****	**0.068*****	**-0.133*****
	(0.044)	**(0.152)**	**(0.023)**	**(0.025)**	**(0.085)**	**(0.013)**
Employment status (reference: employed)						
Unemployed	**-0.059*****	**0.047*****	**-0.034****	**-0.055*****	**0.086*****	**-0.019****
	(0.071)	**(0.248)**	**(0.039)**	**(0.046)**	**(0.156)**	**(0.023)**
Retired	0.030	**-0.039***	-0.004	**0.030***	-0.024	0.016
	(0.075)	**(0.273)**	(0.043)	**(0.065)**	(0.222)	(0.033)
Caring for family	0.015	0.008	-0.021	0.008	0.015	-0.003
	(0.071)	(0.254)	(0.040)	(0.051)	(0.173)	(0.025)
In training	-0.006	-0.009	**-0.029***	0.017	0.015	0.003
	(0.083)	(0.284)	**(0.045)**	(0.055)	(0.187)	(0.028)
Other	**-0.022***	0.002	-0.009	-0.000	0.006	0.001
	(0.149)	(0.626)	(0.099)	(0.104)	(0.355)	(0.053)
House type (reference category: detached)						

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Semi-detached	**-0.056*** **(0.076)**	-0.008 (0.277)	0.000 (0.043)	-	-	-
Terraced	-0.039 (0.082)	-0.016 (0.294)	-0.003 (0.046)	-	-	-
Flat	-0.038 (0.088)	0.003 (0.316)	-0.012 (0.049)	-	-	-
Other	**-0.032*** **(0.131)**	0.011 (0.479)	-0.003 (0.075)	-	-	-
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.017 (0.064)	**0.029**** **(0.224)**	-0.011 (0.035)	0.014 (0.043)	-0.009 (0.147)	-0.009 (0.021)
3 $\geq$ rooms per person	0.006 (0.053)	**-0.030*** **(0.185)**	0.020 (0.029)	-0.002 (0.049)	0.009 (0.167)	**-0.016*** **(0.025)**
Commuting time (reference category: None)						
$\leq$ 15 mins	0.007 (0.058)	-0.014 (0.210)	-0.001 (0.033)	-0.002 (0.043)	**-0.016*** **(0.146)**	0.011 (0.022)
16-30 mins	0.024 (0.057)	**-0.031*** **(0.208)**	-0.002 (0.033)	-0.007 (0.040)	-0.004 (0.134)	0.008 (0.020)
31-50 mins	0.023 (0.061)	-0.025 (0.223)	-0.000 (0.035)	-0.006 (0.041)	-0.004 (0.140)	0.004 (0.021)
$\geq$ 50 mins	0.020 (0.061)	-0.005 (0.224)	-0.015 (0.035)	-0.005 (0.041)	0.002 (0.139)	0.002 (0.021)
Other						
Wave	**-0.048***** **(0.005)**	**0.064***** **(0.017)**	**-0.112***** **(0.003)**	0.012 (0.005)	0.002 (0.016)	**-0.053***** **(0.002)**
R_2	0.04	0.03	0.12	0.05	0.07	0.23

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Observations	8,469	13,622	13,077	34,061	34,947	41,807
Individuals	1,589	2,139	2,162	10,414	10,764	12,053
Mean obs per individual	5.3	6.3	6	3.3	3.2	3.4

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

Table S5.5. Distance decay regression results, showing standardised coefficients (full results from Distance only model).

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Distance only	0.007	0.010	-0.004	-0.010	0.016	0.005
	(2.576)	(8.003)	(1.236)	(0.051)	(0.176)	(0.027)
Area	0.007	0.008	-0.006	-0.009	0.015	0.004
	(0.664)	(2.111)	(0.326)	(0.013)	(0.043)	(0.007)
Habitat types						
ACDG	-0.039	-0.032	-0.029	0.178	-0.049	0.007
Acid grassland	(0.001)	(0.004)	(0.001)	(0.001)	(0.004)	(0.000)
ALTA	0.007	-0.015	0.012	0.023	-0.000	**-0.033***
Allotments	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	**(0.000)**
AMNG	-0.006	0.011	-0.012	0.002	0.005	0.003
Amenity grassland	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
ARBL	0.003	0.023	**-0.026***	**-0.156***	0.091	-0.065
Arable	(0.001)	(0.003)	**(0.000)**	**(0.001)**	(0.002)	(0.000)
BASG	0.013	0.029	0.026	0.013	0.001	0.011
Chalk grassland	(0.005)	(0.006)	(0.001)	(0.002)	(0.007)	(0.001)
BATH	**-0.035***	0.006	0.001	-0.004	0.004	-0.003
Bare artificial	**(0.001)**	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
BOGG	-0.029	-0.007	-0.004	2.610	-1.266	2.143
Bogg	(5.171)	(1.544)	(0.237)	(7.099)	(24.252)	(3.686)
BRAK	0.030	0.047	-0.028	-0.163	0.111	-0.109
Bracken	(0.044)	(0.153)	(0.023)	(0.047)	(0.160)	(0.024)
BSAR	0.006	**0.035***	**-0.037****	-0.001	0.001	-0.006
Bare ground	(0.001)	**(0.004)**	**(0.001)**	(0.000)	(0.000)	(0.000)
CONW	-0.005	0.018	-0.008	**0.024****	**-0.016***	0.002
Conifer woodland	(0.015)	(0.058)	(0.009)	**(0.002)**	**(0.007)**	(0.001)
DTWF	-0.009	-0.013	-0.011	**-0.060*****	-0.012	0.000
Ditch	(0.008)	(0.040)	(0.006)	**(0.001)**	(0.004)	(0.001)
FNCR	0.002	**0.020***	**-0.031*****	-0.012	**0.040****	-0.004
Carr	(0.003)	**(0.016)**	**(0.002)**	(0.039)	**(0.133)**	(0.016)
HINA	0.001	-0.007	-0.003	-0.024	0.031	0.041
Not available	(0.076)	(0.323)	(0.050)	(0.037)	(0.126)	(0.020)
HTHL	-1.265	0.179	0.425	0.001	0.022	-0.002
Heath	(0.706)	(1.536)	(0.238)	(0.015)	(0.052)	(0.008)
IMSS	-0.001	0.001	-0.003	-0.005	-0.009	0.017
Intertidal	(0.012)	(0.058)	(0.009)	(0.003)	(0.012)	(0.002)
IRAG	-0.029	0.029	0.013	**-0.135***	0.082	-0.023
Imp-agri grassland	(0.001)	(0.002)	(0.000)	**(0.000)**	(0.001)	(0.000)
NHRG	0.000	**0.025***	**-0.031****	-0.022	0.009	-0.010
Herb-rich grassland	(0.001)	**(0.005)**	**(0.001)**	(0.001)	(0.003)	(0.000)
NNBW	-0.002	**0.025***	**-0.030****	-0.455	0.549	0.174
Non-native woodland	(0.000)	**(0.001)**	**(0.000)**	(0.000)	(0.002)	(0.000)
NNHD	-0.001	-0.003	-0.013	0.016	0.014	-0.006
Non-native hedge	(0.028)	(0.109)	(0.017)	(0.008)	(0.026)	(0.004)
NSIG	0.008	-0.013	-0.010	-0.013	0.007	-0.012

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
Semi-impr grassland	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
NTSV Not surveyed	-0.031 (0.003)	0.008 (0.008)	0.002 (0.001)	0.010 (0.000)	-0.009 (0.000)	**-0.010*** **(0.000)**
NVBW Native woodland	0.001 (0.000)	**0.025*** **(0.000)**	**-0.031***** **(0.000)**	-0.007 (0.000)	-0.003 (0.000)	-0.004 (0.000)
NVHD Native hedge	0.010 (0.006)	-0.003 (0.025)	0.007 (0.004)	-0.016 (0.001)	0.027 (0.005)	-0.036 (0.001)
NWAS Woodland & scrub	0.380 (10.977)	0.017 (0.352)	-0.008 (0.054)	**-0.040*** **(0.014)**	0.014 (0.047)	0.003 (0.008)
ORCH Orchard	-0.016 (0.003)	0.016 (0.016)	0.006 (0.003)	-0.012 (0.071)	0.017 (0.242)	0.014 (0.033)
OTHR Other	**0.032*** **(0.059)**	0.010 (0.004)	-0.003 (0.001)	-0.001 (0.000)	0.001 (0.000)	-0.006 (0.000)
PLSH Shrubbery	-0.011 (0.007)	-0.010 (0.016)	0.001 (0.002)	0.029 (0.002)	**0.202*** **(0.005)**	**0.194***** **(0.001)**
RDEP Ruderal	-0.020 (0.003)	0.036 (0.009)	**-0.054**** **(0.001)**	-0.001 (0.000)	0.001 (0.000)	-0.006 (0.000)
RDSW Reed	-0.003 (0.054)	-0.038 (0.237)	-0.038 (0.036)	-0.010 (0.004)	-0.017 (0.013)	0.017 (0.002)
RGHL Roughland	0.007 (0.001)	**0.027*** **(0.005)**	-0.001 (0.001)	-0.002 (0.000)	0.002 (0.000)	-0.007 (0.000)
RWRS River	-0.001 (0.003)	0.002 (0.012)	0.000 (0.002)	**-0.045***** **(0.000)**	-0.005 (0.001)	-0.004 (0.000)
SCRB Scrub	0.003 (0.000)	**0.037*** **(0.001)**	**-0.046**** **(0.000)**	-0.087 (0.000)	0.011 (0.000)	-0.039 (0.000)
SCTR Scat trees	0.018 (0.001)	0.001 (0.003)	-0.012 (0.000)	-0.014 (0.000)	0.012 (0.000)	-0.007 (0.000)
STMS Saltmarsh	0.092 (2.286)	0.008 (0.681)	**-0.026*** **(0.102)**	**-0.040*** **(0.049)**	0.014 (0.169)	0.003 (0.027)
STWC Still water	0.018 (0.002)	0.001 (0.007)	-0.025 (0.001)	-0.011 (0.000)	0.003 (0.000)	-0.023 (0.000)
TLHB Tall herb	0.041 (0.002)	0.006 (0.008)	-0.024 (0.001)	-0.005 (0.000)	0.002 (0.000)	-0.015 (0.000)
TYSW Swamp	-0.014 (0.023)	-0.002 (0.103)	-0.006 (0.016)	-0.019 (0.006)	0.008 (0.021)	-0.016 (0.002)
VEGW Vegetated walls	0.013 (0.052)	-0.014 (0.190)	-0.019 (0.029)	-0.107 (0.016)	0.312 (0.051)	-0.207 (0.008)
WOOD Woodland	-0.001 (0.120)	-0.009 (0.559)	0.016 (0.089)	-0.015 (0.015)	0.004 (0.050)	-0.036 (0.008)
WTMV Wet marginal	-0.021 (0.042)	0.020 (0.163)	-0.029 (0.024)	-0.018 (0.001)	-0.011 (0.002)	0.006 (0.000)
Habitat categories						
Grassland	-0.011 (0.000)	0.021 (0.000)	-0.015 (0.000)	0.000 (0.000)	0.007 (0.000)	0.002 (0.000)
Maintained	-0.004 (0.000)	0.010 (0.001)	-0.012 (0.000)	0.001 (0.000)	0.006 (0.000)	0.001 (0.000)
Use	-0.003	0.010	-0.012	0.002	0.006	0.003

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Water	0.014	0.004	-0.021	-0.016	0.003	-0.023
	(0.002)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)
Wet	-0.019	-0.006	-0.032	**-0.046***	-0.016	0.004
	(0.006)	(0.028)	(0.004)	**(0.000)**	(0.002)	(0.000)
Wild	0.002	**0.041***	**-0.044****	-0.002	0.002	-0.009
	(0.000)	**(0.001)**	**(0.000)**	(0.000)	(0.000)	(0.000)
Woodland	0.001	**0.025***	**-0.032*****	-0.015	-0.004	-0.009
	(0.000)	**(0.000)**	**(0.000)**	(0.000)	(0.000)	(0.000)
Habitat diversity						
Habitat richness	0.009	-0.002	-0.007	-0.008	0.022	0.006
	(1.368)	(4.910)	(0.764)	(0.045)	(0.154)	(0.024)
Habitat Shannon's	0.001	-0.014	-0.010	-0.048	0.044	0.005
	(12.433)	(39.082)	(6.043)	(0.344)	(1.177)	(0.184)
Habitat Simpson's	-0.002	-0.014	-0.009	-0.051	0.038	0.003
	(24.497)	(76.000)	(11.733)	(0.590)	(2.016)	(0.318)
Biodiversity						
Butterfly richness	0.013	0.014	-0.018	-0.009	0.013	-0.001
	(3.212)	(11.887)	(1.828)	(0.200)	(0.680)	(0.106)
Bird richness	0.006	-0.000	-0.009	-0.005	0.002	-0.007
	(1.431)	(5.677)	(0.906)	(0.059)	(0.201)	(0.032)
Plant richness	-0.003	-0.002	0.004	-0.008	0.007	0.001
	(0.338)	(1.063)	(0.165)	(0.012)	(0.041)	(0.006)
Total species richness	0.000	-0.001	0.001	-0.008	0.006	-0.000
	(0.270)	(0.896)	(0.140)	(0.011)	(0.038)	(0.006)
NDVI						
NDVI mean	0.012	0.007	-0.008	-0.015	0.021	0.006
	(4.439)	(14.635)	(2.265)	(0.134)	(0.457)	(0.070)
NDVI std	0.011	0.001	-0.015	-0.011	0.030	0.009
	(31.669)	(103.205)	(15.897)	(0.469)	(1.602)	(0.248)
Spatial control variables						
Income deprivation	-0.064	**-0.113***	**-0.157*****	-0.034	-0.037	-0.028
	(0.713)	**(2.614)**	**(0.409)**	(0.612)	(2.077)	(0.303)
Employment deprivation	0.083	0.077	**0.113****	0.024	0.022	0.017
	(1.332)	(4.807)	**(0.749)**	(1.254)	(4.253)	(0.621)
Education deprivation	-0.038	0.050	0.023	-0.006	0.015	-0.016
	(0.004)	(0.014)	(0.002)	(0.004)	(0.013)	(0.002)
Crime deprivation	-0.033	0.005	0.012	0.028	0.032	0.021
	(0.060)	(0.203)	(0.032)	(0.051)	(0.174)	(0.026)
NO_2	-0.007	0.044	-0.013	0.008	0.008	-0.004
	(0.006)	(0.019)	(0.003)	(0.005)	(0.016)	(0.002)
Age (yrs) (reference category: 46-55yrs)						
16-25	**-0.105****	0.032	**-0.085****	-0.016	0.014	-0.032
	(0.123)	(0.440)	**(0.069)**	(0.101)	(0.340)	(0.051)

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
26-35	**-0.099***** **(0.092)**	**0.050*** **(0.327)**	-0.041 (0.051)	-0.008 (0.073)	0.016 (0.248)	-0.010 (0.037)
36-45	**-0.063***** **(0.061)**	**0.034*** **(0.215)**	-0.002 (0.033)	-0.011 (0.048)	0.001 (0.162)	-0.003 (0.024)
56-65	**0.042*** **(0.062)**	**-0.061***** **(0.222)**	0.013 (0.035)	0.023 (0.057)	**-0.031**** **(0.194)**	-0.010 (0.029)
66-75	0.040 (0.107)	**-0.044*** **(0.379)**	-0.003 (0.059)	**0.040*** **(0.092)**	**-0.041**** **(0.312)**	0.002 (0.047)
75+	0.008 (0.147)	-0.022 (0.528)	-0.026 (0.082)	0.031 (0.132)	-0.021 (0.448)	-0.010 (0.067)
University-level qualification	**-0.084*** **(0.110)**	0.012 (0.339)	-0.002 (0.053)	-0.034 (0.072)	0.012 (0.246)	-0.012 (0.037)
In a relationship	**0.099***** **(0.052)**	**-0.044**** **(0.181)**	0.018 (0.028)	0.026 (0.048)	-0.005 (0.163)	-0.009 (0.024)
Living with children	-0.020 (0.051)	-0.011 (0.178)	0.000 (0.028)	-0.010 (0.043)	0.004 (0.147)	-0.008 (0.022)
Annual household income	-0.009 (0.019)	0.003 (0.074)	**-0.030**** **(0.012)**	0.009 (0.017)	**-0.018*** **(0.057)**	-0.001 (0.008)
Health condition	**-0.116***** **(0.044)**	**0.135***** **(0.152)**	**-0.231***** **(0.023)**	**-0.043***** **(0.025)**	**0.068***** **(0.085)**	**-0.133***** **(0.013)**
Employment status (reference: employed)						
Unemployed	**-0.059***** **(0.071)**	**0.047***** **(0.248)**	**-0.034**** **(0.039)**	**-0.055***** **(0.046)**	**0.086***** **(0.156)**	**-0.019**** **(0.023)**
Retired	0.030 (0.075)	**-0.039*** **(0.273)**	-0.004 (0.043)	**0.030*** **(0.065)**	-0.024 (0.222)	0.016 (0.033)
Caring for family	0.015 (0.071)	0.009 (0.254)	-0.021 (0.040)	0.008 (0.051)	0.015 (0.173)	-0.003 (0.025)
In training	-0.006 (0.083)	-0.010 (0.284)	-0.029* (0.045)	0.017 (0.055)	0.015 (0.187)	0.003 (0.028)
Other	**-0.022*** **(0.149)**	0.002 (0.626)	-0.008 (0.099)	-0.000 (0.104)	0.006 (0.355)	0.001 (0.053)
House type (reference category: detached)						
Semi-detached	**-0.057*** **(0.076)**	-0.007 (0.277)	-0.001 (0.043)	-	-	-
Terraced	-0.040 (0.082)	-0.016 (0.294)	-0.004 (0.046)	-	-	-
Flat	-0.038 (0.088)	0.002 (0.316)	-0.012 (0.049)	-	-	-
Other	**-0.032*** **(0.131)**	0.010 (0.479)	-0.003 (0.075)	-	-	-
Household space (reference category: 1 - < 3 rooms per person)						
<1 room per person	-0.017	**0.029****	-0.011	0.014	-0.009	-0.009

	BHPS			UKHLS		
	Life satisfaction	GHQ	General health	Life satisfaction	GHQ	General health
	(0.064)	**(0.224)**	(0.035)	(0.043)	(0.147)	(0.021)
3 ≥ rooms per person	0.006	**-0.029***	0.019	-0.002	0.009	**-0.016***
	(0.053)	**(0.185)**	(0.029)	(0.049)	(0.167)	**(0.025)**
Commuting time (reference category: None)						
≤ 15 mins	0.007	-0.014	-0.001	-0.002	**-0.016***	0.011
	(0.058)	(0.210)	(0.033)	(0.043)	**(0.146)**	(0.022)
16-30 mins	0.024	**-0.031***	-0.002	-0.007	-0.004	0.008
	(0.057)	**(0.208)**	(0.033)	(0.040)	(0.134)	(0.020)
31-50 mins	0.022	-0.025	-0.000	-0.006	-0.004	0.004
	(0.061)	(0.223)	(0.035)	(0.041)	(0.140)	(0.021)
≥ 50 mins	0.020	-0.005	-0.014	-0.005	0.002	0.002
	(0.061)	(0.224)	(0.035)	(0.041)	(0.139)	(0.021)
Other						
Wave	**-0.047****	**0.064*****	**-0.111*****	0.012	0.002	**-0.053*****
	(0.005)	**(0.016)**	**(0.003)**	(0.005)	(0.016)	**(0.002)**
R^2	0.04	0.03	0.13	0.05	0.07	0.24
Observations	8,469	13,622	13,077	34,061	34,947	41,087
Individuals	1,589	2,139	2,162	10,414	10,764	12,053
Mean obs per person	5.3	6.4	6	3.3	3.2	3.4

Standard errors in parentheses
*p<0.001, **p<0.01, ***p<0.05

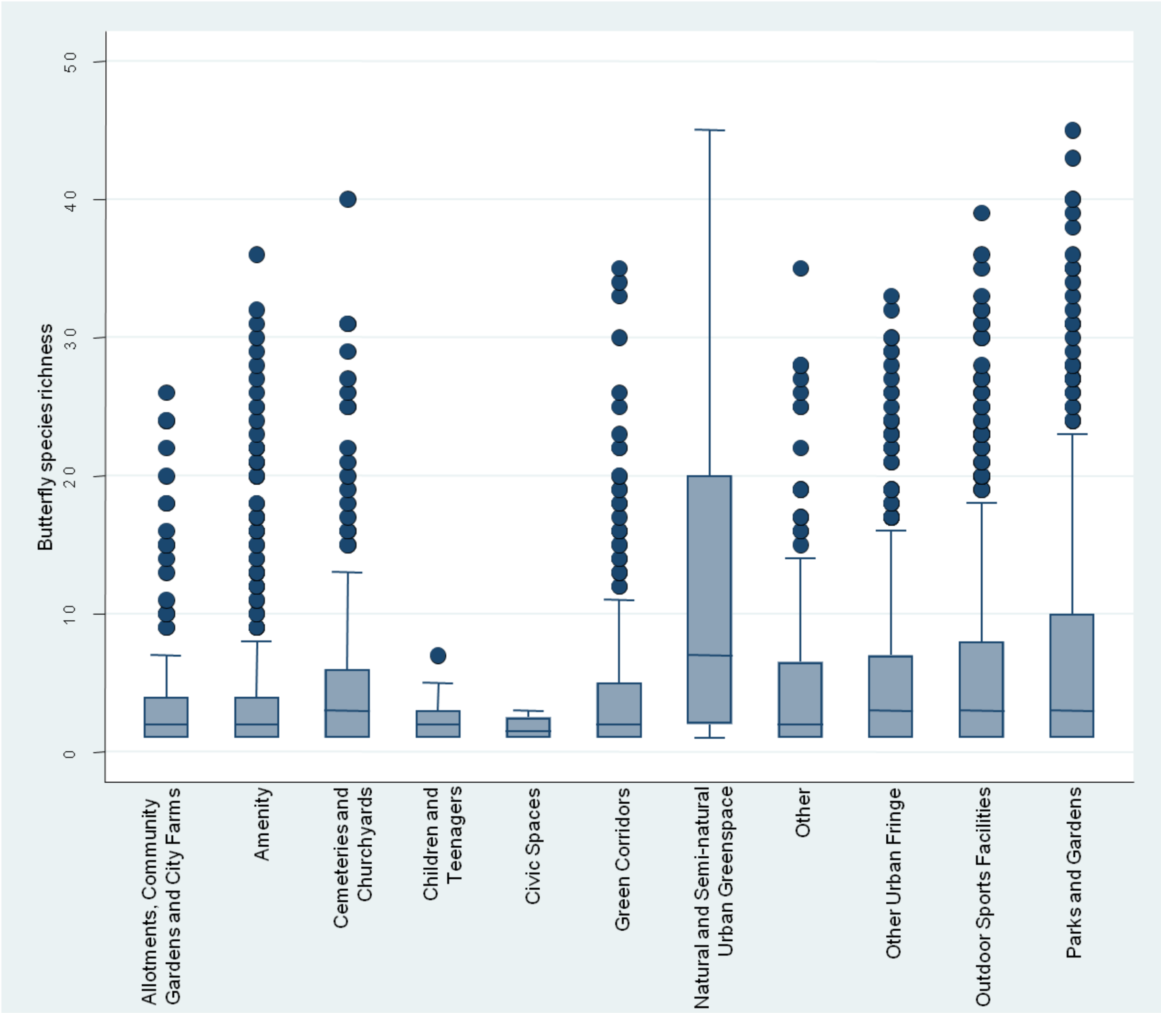

Figure S5.8. Butterfly species richness for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

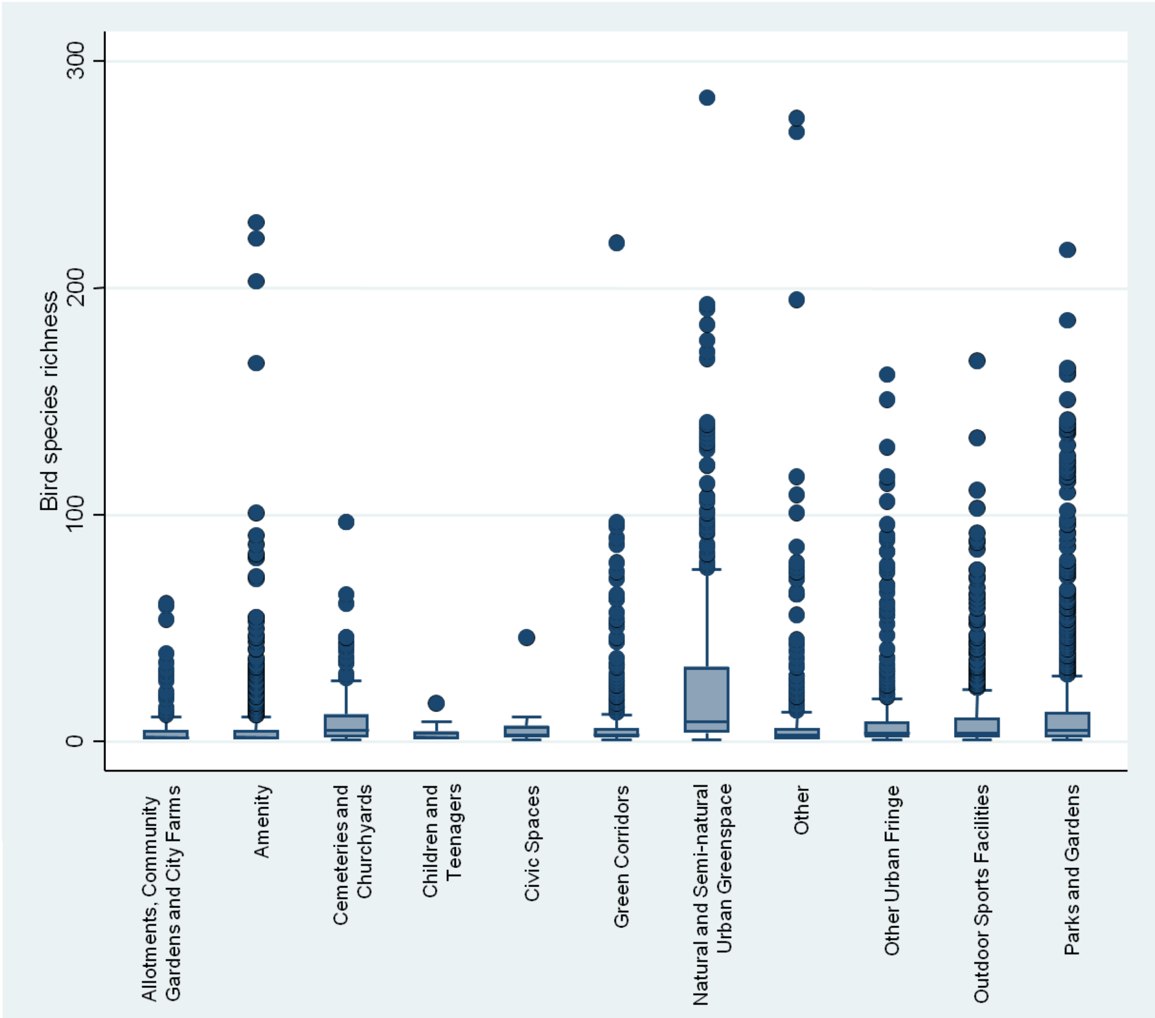

Figure S5.9. Bird species richness for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

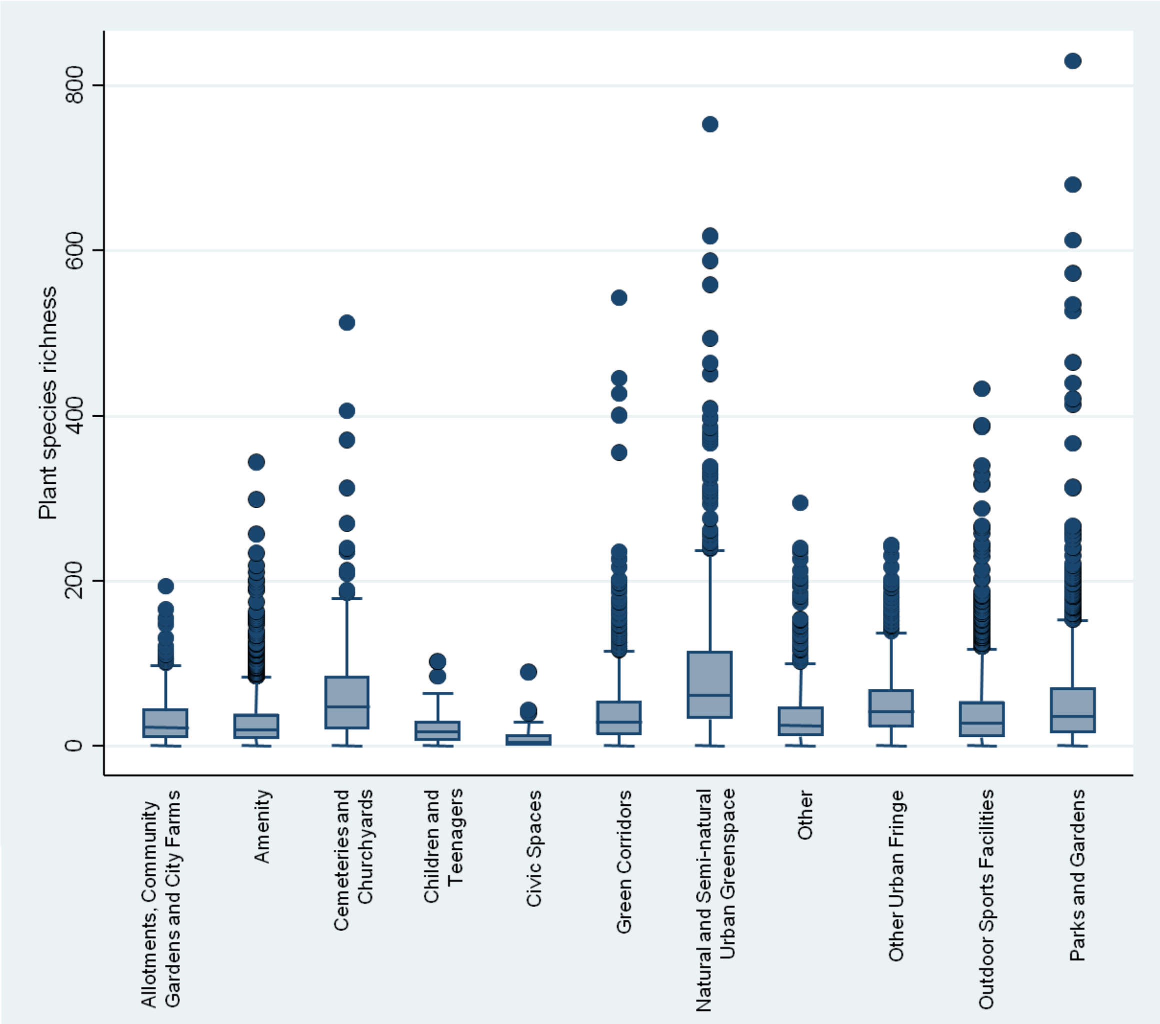

Figure S5.10. Plant species richness for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

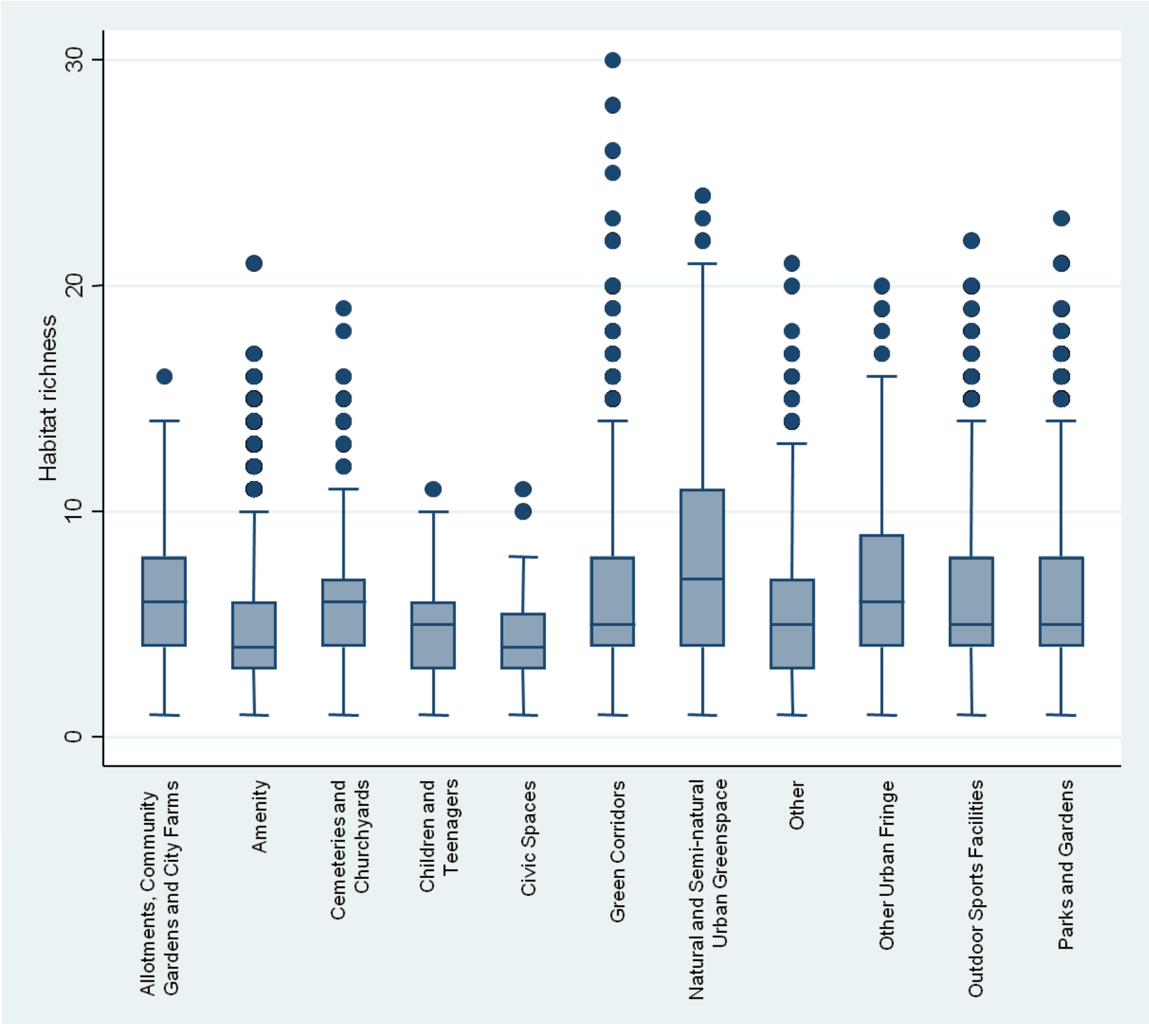

Figure S5.11. The number of habitats for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

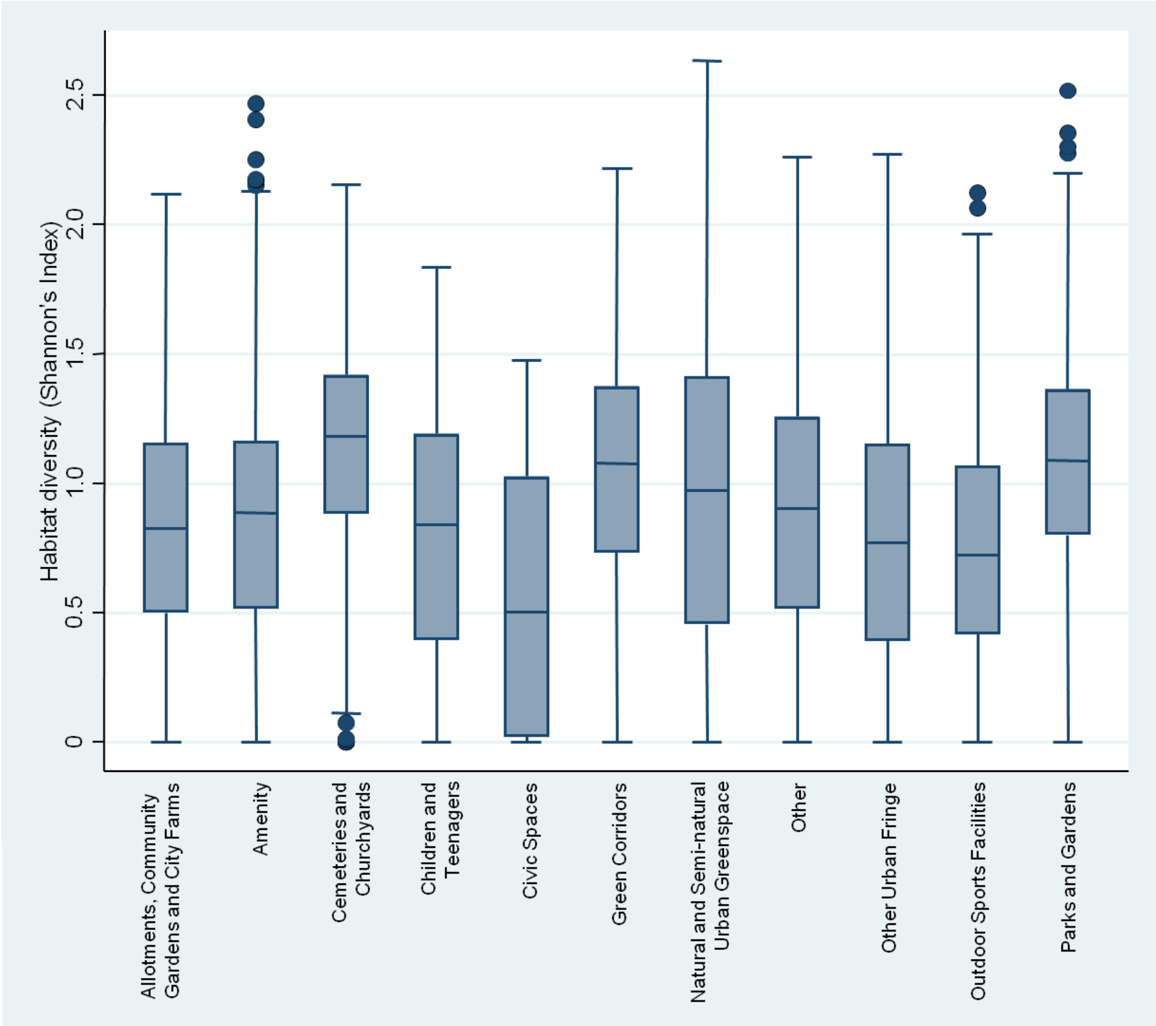

Figure S5.12. Habitat diversity (Shannon's Index) for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

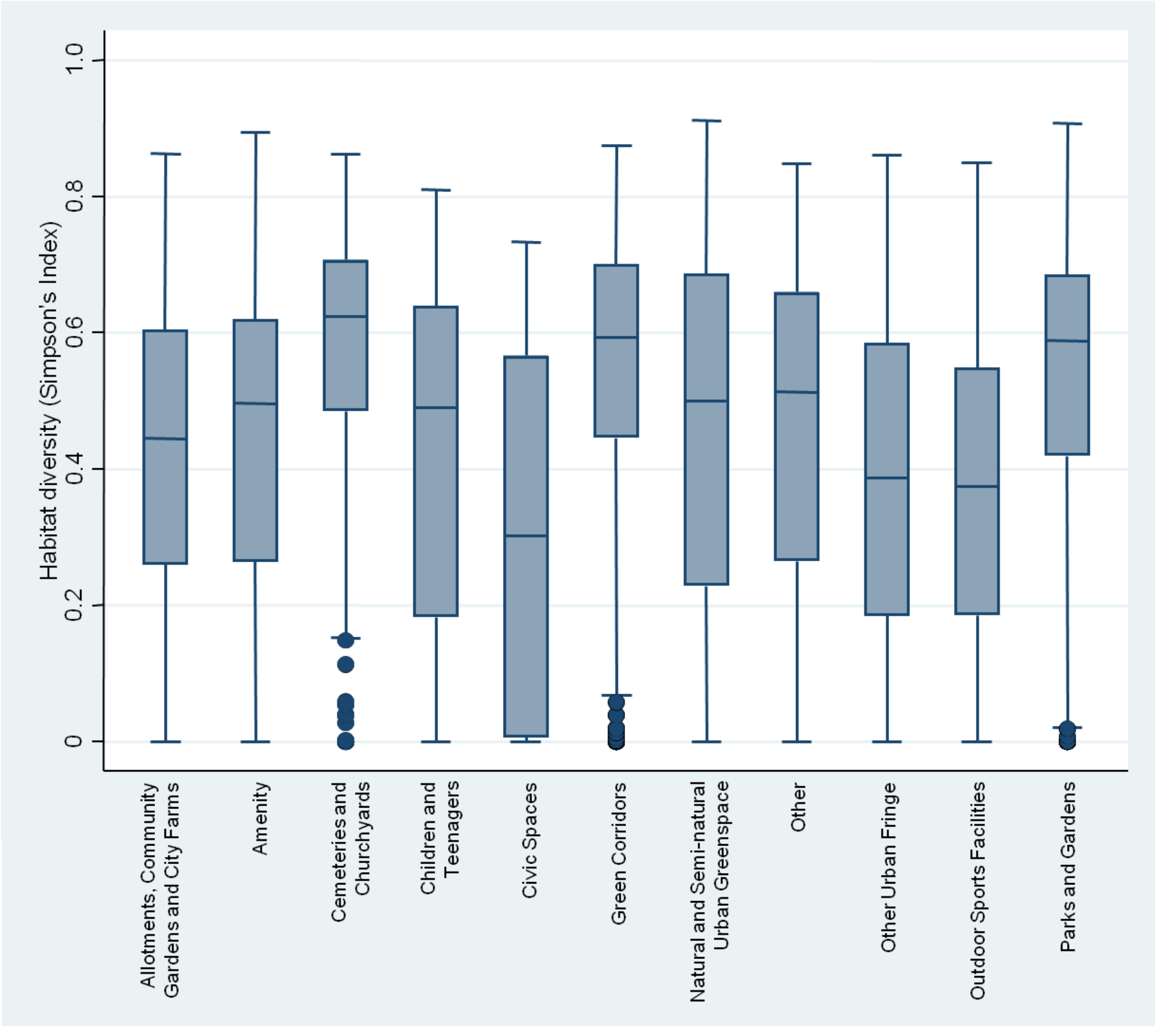

Figure S5.13. Habitat diversity (Simpson's Index) for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

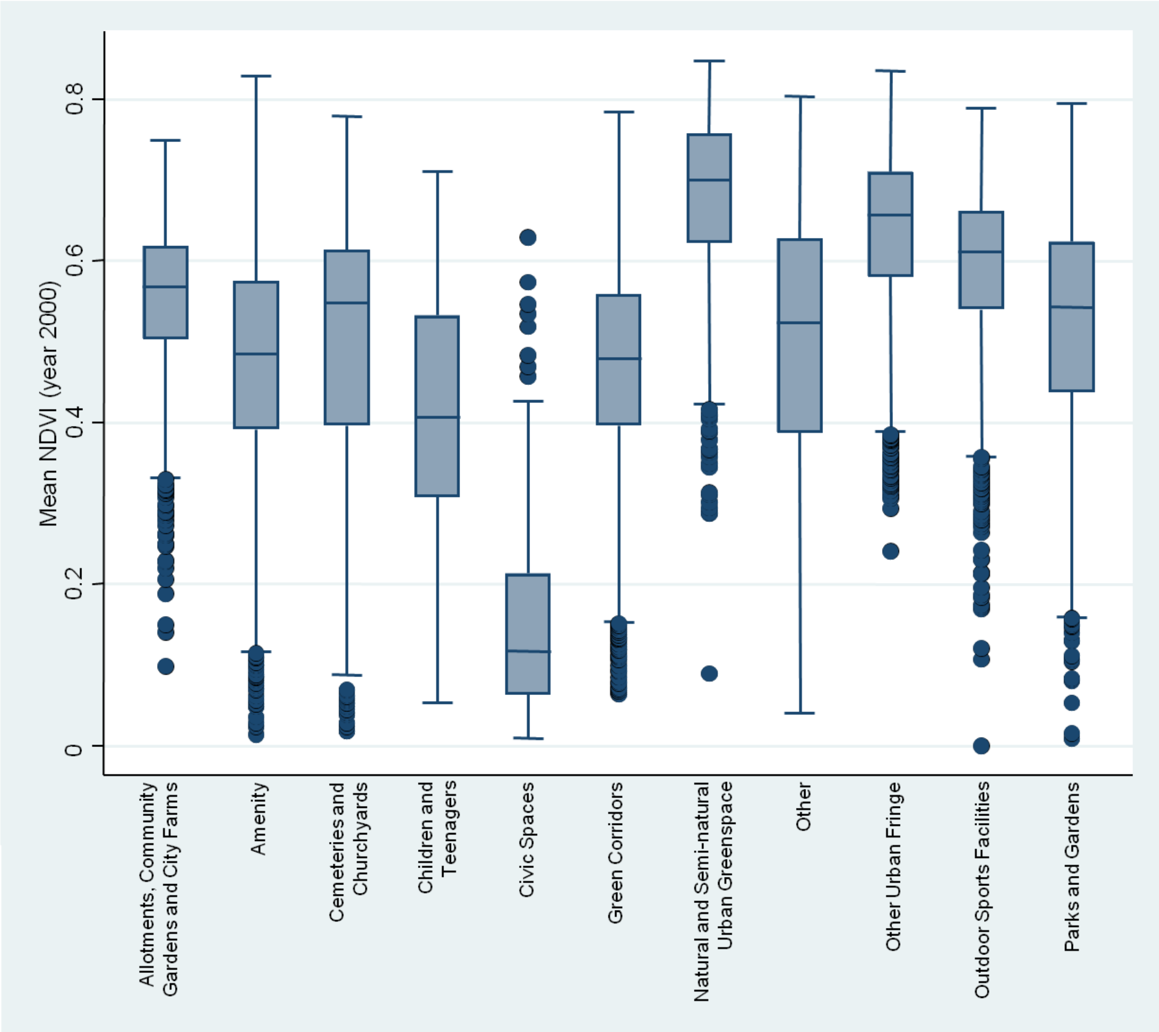

Figure S5.14. Mean NDVI in the year 2000 for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

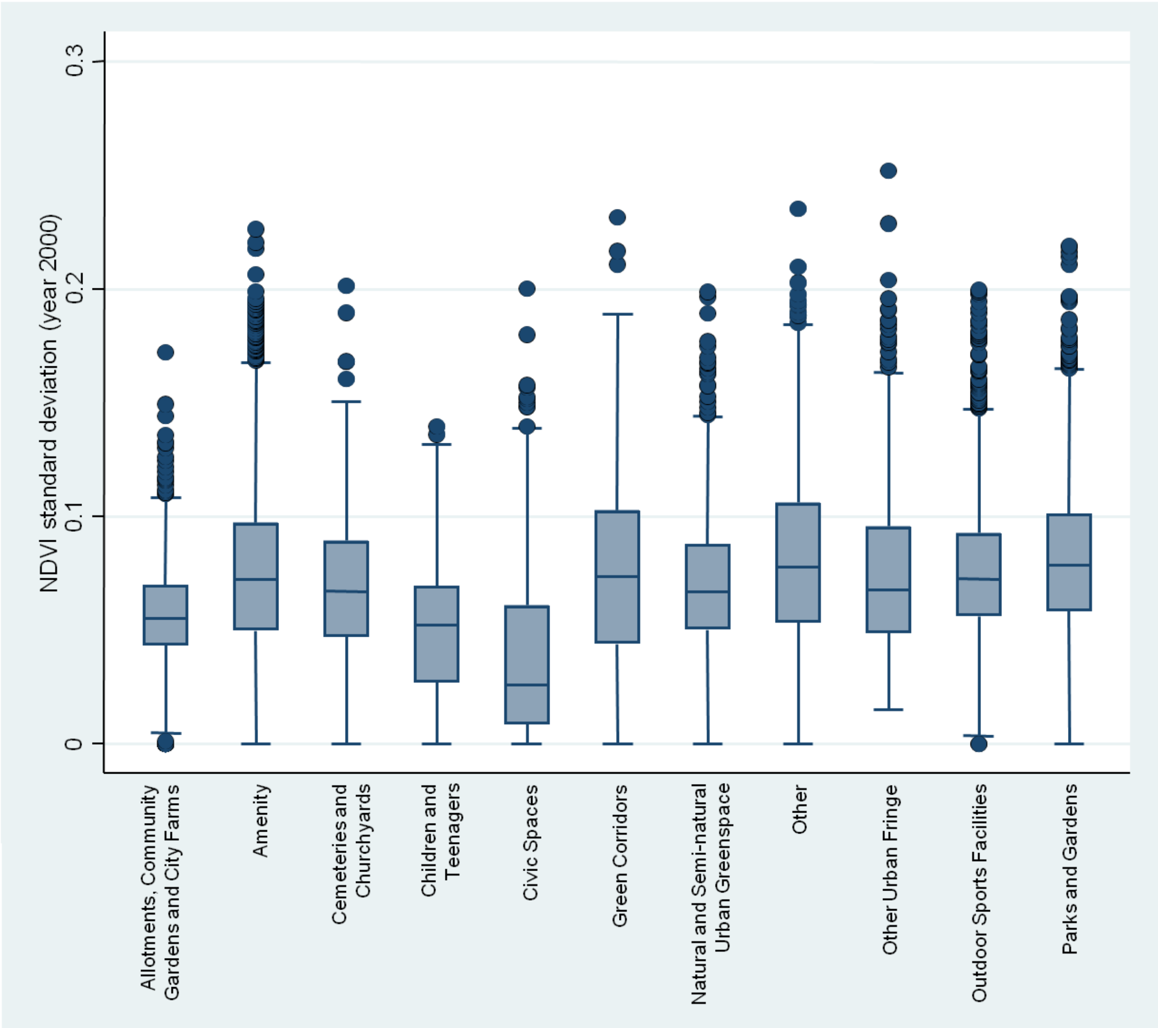

Figure S5.15. NDVI standard deviation in the year 2000 for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

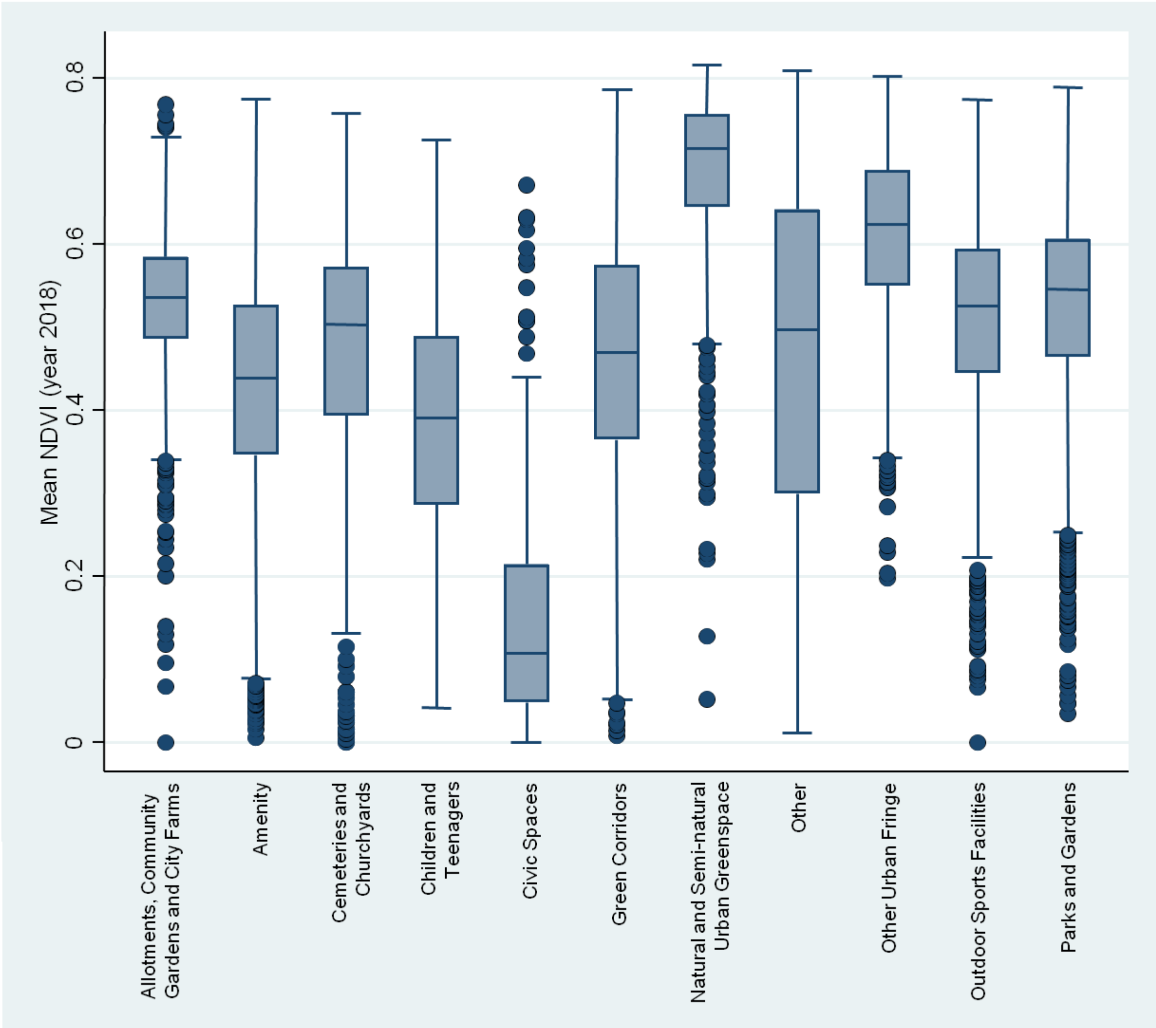

Figure S5.16. Mean NDVI in the year 2018 for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

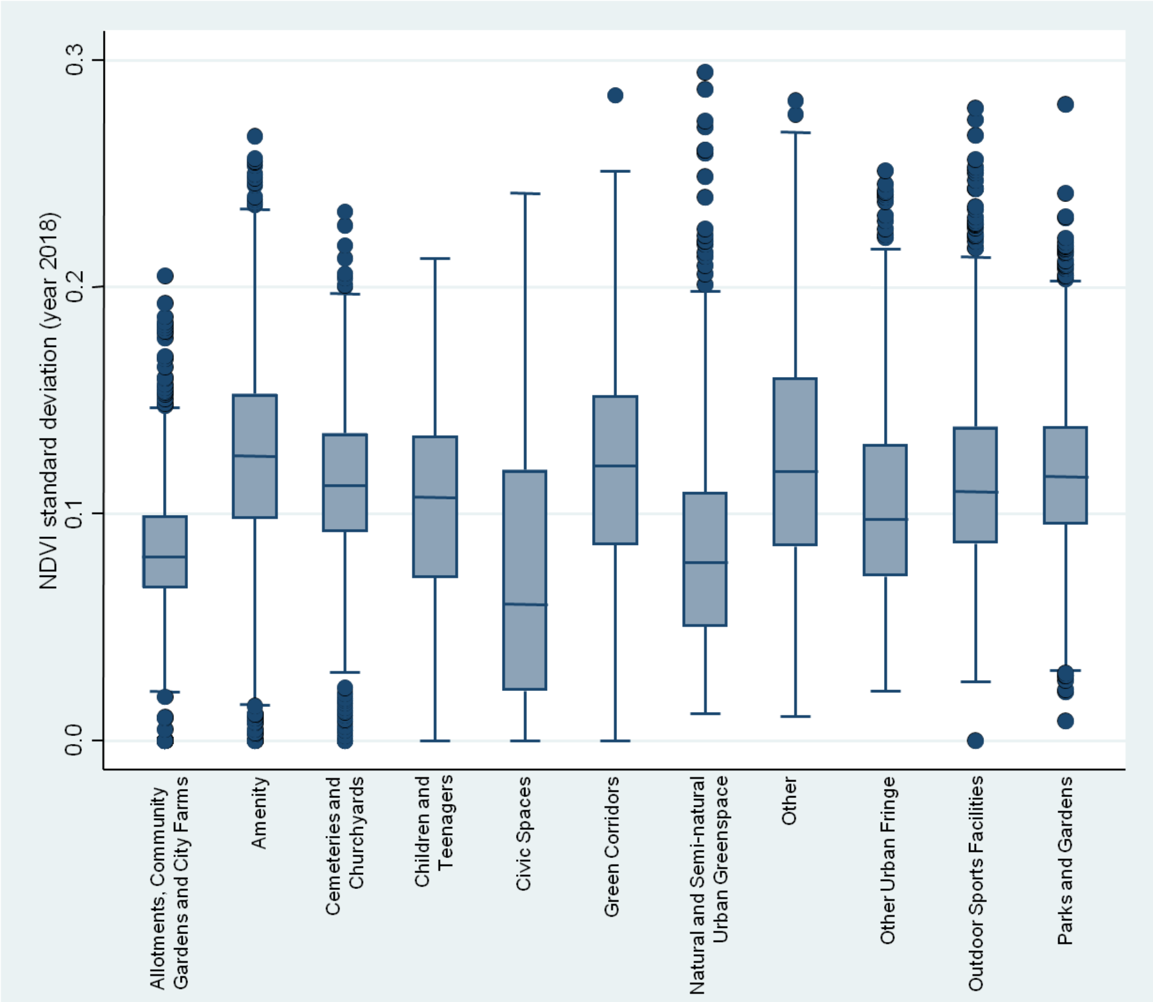

Figure S5.17. NDVI standard deviation in the year 2018 for all Open Space Sites (OSSs) in Greater London, by Planning Policy Guidance 17 (PPG17) category.

References

Adler, M. D., Dolan, P., & Kavetsos, G. (2017). Would you choose to be happy? Tradeoffs between happiness and the other dimensions of life in a large population survey. *Journal of Economic Behavior and Organization*, **139**, 60–73.

Aerts, R., Honnay, O., & Van Nieuwenhuyse, A. (2018). Biodiversity and human health: Mechanisms and evidence of the positive health effects of diversity in nature and green spaces. *British Medical Bulletin*, **127**(1), 5–22.

Akpinar, A. (2016). How is quality of urban green spaces associated with physical activity and health? *Urban Forestry and Urban Greening*, **16**, 76–83.

Akpinar, A., Barbosa-Leiker, C., & Brooks, K. R. (2016). Does green space matter? Exploring relationships between green space type and health indicators. *Urban Forestry and Urban Greening*, **20**, 407–418.

Alcock, I., White, M. P., Lovell, R., … Wheeler, B. W. (2015). What accounts for 'England's green and pleasant land'? A panel data analysis of mental health and land cover types in rural England. *Landscape and Urban Planning*, **142**, 38–46.

Alcock, I., White, M. P., Wheeler, B. W., Fleming, L. E., & Depledge, M. H. (2014). Longitudinal Effects on Mental Health of Moving to Greener and Less Green Urban Areas. *Environmental Science & Technology*, **48**, 1247–1255.

Ambrey, C., & Fleming, C. (2013). Public Greenspace and Life Satisfaction in Urban Australia. *Urban Studies*, **51**(6), 1290–1321.

Ambrey, C. L., & Fleming, C. M. (2011). Valuing scenic amenity using life satisfaction data. *Ecological Economics*, **72**, 106–115.

Ambrey, C. L., & Fleming, C. M. (2014). Valuing Ecosystem Diversity in South East Queensland: A Life Satisfaction Approach. *Social Indicators Research*, **115**(1), 45–65.

Ambrey, C. L., Fleming, C. M., & Chan, A. Y. C. (2014). Estimating the cost of air pollution in South East Queensland: An application of the life satisfaction non-market valuation approach. *Ecological Economics*, **97**, 172–181.

Angold, P. G., Sadler, J. P., Hill, M. O., … Thompson, K. (2006). Biodiversity in urban habitat patches. *Science of the Total Environment*, **360**, 196–204.

Annerstedt, M., Östergren, P. O., Björk, J., Grahn, P., Skärbäck, E., & Währborg, P. (2012).

Green qualities in the neighbourhood and mental health - Results from a longitudinal cohort study in Southern Sweden. *BMC Public Health*, **12**(1), 1.

Annerstedt Van Den Bosch, M., Egorov, A. I., Mudu, P., … Zurlyte, I. (2016). Development of an urban green space indicator and the public health rationale. *Scandinavian Journal of Public Health*, **44**(2), 159–167.

Aronson, M. F. J., Lepczyk, C. A., Evans, K. L., … Vargo, T. (2017). Biodiversity in the city: key challenges for urban green space management. *Frontiers in Ecology and the Environment*, **15**(4), 189–196.

Aspinall, P., Mavros, P., Coyne, R., & Roe, J. (2015). The urban brain: analysing outdoor physical activity with mobile EEG. *British Journal of Sports Medicine*, **49**, 272–276.

Astell-Burt, T., & Feng, X. (2019). Association of Urban Green Space with Mental Health and General Health among Adults in Australia. *JAMA Network Open*, **2**(7), 1–22.

Astell-Burt, T., Feng, X., & Kolt, G. S. (2014a). Green space is associated with walking and moderate-to-vigorous physical activity (MVPA) in middle-to-older-aged adults: Findings from 203 883 Australians in the 45 and Up Study. *British Journal of Sports Medicine*, **48**(5), 404–406.

Astell-Burt, T., Feng, X., & Kolt, G. S. (2014b). Greener neighborhoods, slimmer people evidence from 246 920 Australians. *International Journal of Obesity*, **38**(1), 156–159.

Astell-Burt, T., Mitchell, R., & Hartig, T. (2014c). The association between green space and mental health varies across the lifecourse. A longitudinal study. *Journal of Epidemiology and Community Health*, **68**(6), 578–83.

Atkinson, G., Groom, B., Hanley, N., & Mourato, S. (2018). Environmental Valuation and Benefit-Cost Analysis in U.K. Policy. *Journal of Benefit-Cost Analysis*, **9**(1), 97–119.

Ayala-Azcárraga, C., Diaz, D., & Zambrano, L. (2019). Characteristics of urban parks and their relation to user well-being. *Landscape and Urban Planning*, **189**, 27–35.

Barrington-Leigh, C., & Behzadnejad, F. (2017a). Evaluating the short-term cost of low-level local air pollution: A life satisfaction approach. *Environmental Economics and Policy Studies*, **19**(2), 269–298.

Barrington-Leigh, C., & Behzadnejad, F. (2017b). The impact of daily weather conditions on life satisfaction: Evidence from cross-sectional and panel data. *Journal of Economic Psychology*, **59**, 145–163.

Bartolini, S., & Sarracino, F. (2018). Do People Care About Future Generations? Derived Preferences from Happiness Data. *Ecological Economics*, **143**, 253–275.

Barton, J., & Pretty, J. (2010). What is the best dose of nature and green exercise for improving mental health- A multi-study analysis. *Environmental Science and Technology*, **44**(10), 3947–3955.

Beelen, R., Raaschou-Nielsen, O., Stafoggia, M., … Hoek, G. (2014). Effects of long-term exposure to air pollution on natural-cause mortality: An analysis of 22 European cohorts within the multicentre ESCAPE project. *The Lancet*, **383**(9919), 785–795.

Bell, S. L., Phoenix, C., Lovell, R., & Wheeler, B. W. (2015a). Seeking everyday wellbeing: The coast as a therapeutic landscape. *Social Science & Medicine*, **142**, 56–67.

Bell, S. L., Phoenix, C., Lovell, R., & Wheeler, B. W. (2015b). Using GPS and geo-narratives: a methodological approach for understanding and situating everyday green space encounters. *Area*, **47**(1), 88–96.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate : A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, **57**, 289–300.

Berman, M., Jonides, J., & Kaplan, S. (2008). The cognitive benefits of interacting with nature. *Psychological Science*, **19**(12), 1207–1212.

Berto, R. (2014). The Role of Nature in Coping with Psycho-Physiological Stress: A Literature Review on Restorativeness. *Behavioral Sciences*, **4**, 394–409.

Biernacka, M., & Kronenberg, J. (2018). Classification of institutional barriers affecting the availability, accessibility and attractiveness of urban green spaces. *Urban Forestry and Urban Greening*, **36**, 22–33.

Bino, G., Levin, N., Darawshi, S., Van Der Hal, N., Reich-Solomon, A., & Kark, S. (2008). Accurate prediction of bird species richness patterns in an urban environment using Landsat-derived NDVI and spectral unmixing. *International Journal of Remote Sensing*, **29**(13), 3675–3700.

Bircher, J., & Kuruvilla, S. (2014). Defining health by addressing individual, social, and environmental determinants: New opportunities for health care and public health. *Journal of Public Health Policy*, **35**(3), 363–386.

Bird, W. (2007). *Natural Thinking*, Royal Society for the Protection of Birds.

Blanchflower, D. G., & Oswald, A. J. (2008). Hypertension and happiness across nations. *Journal of Health Economics*, **27**(2), 218–233.

Bonthoux, S., Balent, G., Augiron, S., Baudry, J., & Bretagnolle, V. (2017). Geographical generality of bird-habitat relationships depends on species traits. *Diversity and Distributions*, **23**(11), 1343–1352.

Bos, E. H., van der Meulen, L., Wichers, M., & Jeronimus, B. F. (2016). A primrose path? Moderating effects of age and gender in the association between green space and mental health. *International Journal of Environmental Research and Public Health*, **13**(13), 492.

Botzat, A., Fischer, L. K., & Kowarik, I. (2016). Unexploited opportunities in understanding liveable and biodiverse cities. A review on urban biodiversity perception and valuation. *Global Environmental Change*, **39**, 220–233.

Bowler, D., Buyung-Ali, L., Knight, T., & Pullin, A. (2010). *How effective is 'greening' of urban areas in reducing human exposure to ground level ozone concentrations, UV exposure and the 'urban heat island effect'? CEE review 08-004 (SR41)*, Environmental Evidence: www.environmentalevidence.org/SR41.html.

Boyd, F., White, M. P., Bell, S. L., & Burt, J. (2018). Who doesn't visit natural environments for recreation and why: A population representative analysis of spatial, individual and temporal factors among adults in England. *Landscape and Urban Planning*, **175**, 102–113.

Bratman, G. N., Anderson, C. B., Berman, M. G., … Daily, G. C. (2019). Nature and mental health: An ecosystem service perspective. *Science Advances*, **5**, eaax0903.

Brauer, M., & Hystad, P. (2014). Commentary: Cities and health⋯Let me count the ways. *Epidemiology*, **25**, 526–527.

Brereton, F., Clinch, J., & Ferreira, S. (2008). Happiness, geography and the environment. *Ecological Economics*, **65**(2), 386–396.

Brindley, P., Cameron, R. W., Ersoy, E., Jorgensen, A., & Maheswaran, R. (2019). Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. *Urban Forestry and Urban Greening*, **39**, 45–54.

Brindley, P., Jorgensen, A., & Maheswaran, R. (2018). Domestic gardens and self-reported health: A national population study. *International Journal of Health Geographics*, **17**(1), 1–11.

Brink, M. (2011). Parameters of well-being and subjective health and their relationship with residential traffic noise exposure--a representative evaluation in Switzerland. *Environment International*, **37**(4), 723–33.

Britton, E., Kindermann, G., Domegan, C., & Carlin, C. (2020). Blue care: A systematic review of blue space interventions for health and wellbeing. *Health Promotion International*, **35**(1), 50–69.

Brook, R. D., Rajagopalan, S., Pope, C. a., … Kaufman, J. D. (2010). Particulate Matter Air Pollution and Cardiovascular Disease: An Update to the Scientific Statement From the American Heart Association. *Circulation*, **121**(21), 2331–2378.

Brown, T. T. (2015). The Subjective Well-Being Method of Valuation: An Application to General Health Status. *Health Services Research*, **50**(6), 1996–2018.

Browning, M., & Lee, K. (2017). Within what distance does "greenness" best predict physical health? A systematic review of articles with gis buffer analyses across the lifespan. *International Journal of Environmental Research and Public Health*, **14**(7), 1–21.

Brun, P., Zimmermann, N. E., Graham, C. H., … Thuiller, W. (2019). The productivity-biodiversity relationship varies across diversity dimensions. *Nature Communications*, **10**(1), 5691.

Brunekreef, B., Künzli, N., Pekkanen, J., … Harrison, R. M. (2015). Clean air in Europe: beyond the horizon? *The European Respiratory Journal*, **45**, 7–10.

Buoli, M., Grassi, S., Caldiroli, A., … Bollati, V. (2018). Is there a link between air pollution and mental disorders? *Environment International*, **118**, 154–168.

Byrne, J., Sipe, N., & Searle, G. (2010). Green around the gills? The challenge of density for urban greenspace planning in SEQ. *Australian Planner*, **47**(3), 162–177.

Cabinet Office. (2013). *Wellbeing Policy and Analysis: An Update of Wellbeing Work across Whitehall*, London.

Callaghan, C. T., Poore, A. G. B., Major, R. E., Rowley, J. J. L., & Cornwell, W. K. (2019). Optimizing future biodiversity sampling by citizen scientists. *Proceedings of the Royal Society B: Biological Sciences*, **286**(1912), 20191487.

Cameron, R. W. F., Blanuša, T., Taylor, J. E., … Thompson, K. (2012). The domestic garden - Its contribution to urban green infrastructure. *Urban Forestry and Urban Greening*, **11**(2), 129–137.

Cameron, R. W. F., Brindley, P., Mears, M., … Richardson, M. (2020). Where the wild things are! Do urban green spaces with greater avian biodiversity promote more positive emotions in humans? *Urban Ecosystems*, **23**(2), 301–317.

Campbell-Arvai, V. (2019). Engaging urban nature: improving our understanding of public perceptions of the role of biodiversity in cities. *Urban Ecosystems*, **22**(2), 409–423.

Capaldi, C. a, Dopko, R. L., & Zelenski, J. M. (2014). The relationship between nature connectedness and happiness : a meta-analysis. *Frontiers in Psychology*, **5**, 976.

Carey, I. M., Atkinson, R. W., Kent, A. J., Van Staa, T., Cook, D. G., & Anderson, H. R. (2013). Mortality associations with long-term exposure to outdoor air pollution in a national English cohort. *American Journal of Respiratory and Critical Care Medicine*, **187**(11), 1226–1233.

Carpiano, R. M., & Hystad, P. W. (2011). "Sense of community belonging" in health surveys: What social capital is it measuring? *Health and Place*, **17**(2), 606–617.

Carrus, G., Scopelliti, M., Lafortezza, R., … Sanesi, G. (2015). Go greener, feel better? The positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. *Landscape and Urban Planning*, **134**, 221–228.

Chang, K. G., Sullivan, W. C., Lin, Y. H., Su, W., & Chang, C. Y. (2016). The effect of biodiversity on green space users' wellbeing-An empirical investigation using physiological evidence. *Sustainability*, **8**, 1049.

Chay, K. Y., & Greenstone, M. (2005). Does Air Quality Matter ? Evidence from the Housing Market Michael Greenstone. *Journal of Political Economy*, **113**(2), 376–424.

Cinderby, S., & Bagwell, S. (2018). Exploring the co-benefits of urban green infrastructure improvements for businesses and workers' wellbeing. *Area*, **50**(1), 126–135.

Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*, **46**(1), 95–144.

Clark, N. E., Lovell, R., Wheeler, B. W., Higgins, S. L., Depledge, M. H., & Norris, K. (2014). Biodiversity, cultural pathways, and human health: A framework. *Trends in Ecology and Evolution*, **29**(4), 198–204.

Cohen, A. J., Brauer, M., Burnett, R., … Forouzanfar, M. H. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, **389**(10082), 1907–1918.

Coldwell, D. F., & Evans, K. L. (2018). Visits to urban green-space and the countryside associate with different components of mental well-being and are better predictors than perceived or actual local urbanisation intensity. *Landscape and Urban Planning*, **175**, 114–122.

Committee on Climate Change. (2019). *Progress in preparing for climate change. 2019 Report to Parliament*, London.

Coombes, E., Jones, A., & Hillsdon, M. (2010). The relationship of physical activity and overweight to objectively measured green space accessibility and use. *Social Science & Medicine*, **70**(6), 816–822.

Cooper, N., Brady, E., Steen, H., & Bryce, R. (2016). Aesthetic and spiritual values of ecosystems: Recognising the ontological and axiological plurality of cultural ecosystem 'services.' *Ecosystem Services*, **21**, 218–229.

Costanza, R. (2014). Time to leave GDP behind. *Nature*, **505**, 283–285.

Coventry, P. A., Neale, C., Dyke, A., Pateman, R., & Cinderby, S. (2019). The Mental Health Benefits of Purposeful Activities in Public Green Spaces in Urban and Semi-Urban Neighbourhoods: A Mixed-Methods Pilot and Proof of Concept Study. *International Journal of Environmental Research and Public Health*, **16**(15), 2712.

Cox, D. T. C., & Gaston, K. J. (2016). Urban bird feeding: Connecting people with nature. *PLoS*

ONE, **11**(7), 1–13.

Cox, D. T. C., Hudson, H. L., Shanahan, D. F., Fuller, R. A., & Gaston, K. J. (2017). The rarity of direct experiences of nature in an urban population. *Landscape and Urban Planning*, **160**, 79–84.

Cox, D. T. C., Shanahan, D. F., Hudson, H. L., Fuller, R. A., & Gaston, K. J. (2018). The impact of urbanisation on nature dose and the implications for human health. *Landscape and Urban Planning*, **179**, 72–80.

Cracknell, D., White, M. P., Pahl, S., & Depledge, M. H. (2017). A preliminary investigation into the restorative potential of public aquaria exhibits: a UK student-based study. *Landscape Research*, **42**(1), 18–32.

Crouse, D. L., Pinault, L., Balram, A., … Villeneuve, P. J. (2017). Urban greenness and mortality in Canada's largest cities: a national cohort study. *The Lancet Planetary Health*, **1**(7), e289–e297.

Culbert, P. D., Radeloff, V. C., St-Louis, V., … Pidgeon, A. M. (2012). Modeling broad-scale patterns of avian species richness across the Midwestern United States with measures of satellite image texture. *Remote Sensing of Environment*, **118**, 140–150.

Czembrowski, P., & Kronenberg, J. (2016). Hedonic pricing and different urban green space types and sizes: Insights into the discussion on valuing ecosystem services. *Landscape and Urban Planning*, **146**, 11–19.

Dadvand, P., & Nieuwenhuijsen, M. (2019). Green Space and Health. In *Integrating Human Health into Urban and Transport Planning*, Cham: Springer, pp. 409–423.

Dadvand, P., Rivas, I., Basagaña, X., … Nieuwenhuijsen, M. J. (2015). The association between greenness and traffic-related air pollution at schools. *Science of the Total Environment*, **523**, 59–63.

Dadvand, P., Wright, J., Martinez, D., … Nieuwenhuijsen, M. J. (2014). Inequality, green spaces, and pregnant women: Roles of ethnicity and individual and neighbourhood socioeconomic status. *Environment International*, **71**, 101–108.

Daily, G. C., Söderqvist, T., Aniyar, S., … Walker, B. (2000). Value of nature and the nature of value. *Science*, **289**(5478), 395–396.

Dallimer, M., Davies, Z. G., Irvine, K. N., … Armsworth, P. R. (2014). What personal and environmental factors determine frequency of urban greenspace use? *International Journal of Environmental Research and Public Health*, **11**(8), 7977–7992.

Dallimer, M., Irvine, K. N., Skinner, A. M. J., … Gaston, K. J. (2012). Biodiversity and the feel-good factor: Understanding associations between self-reported human well-being and species richness. *BioScience*, **62**(1), 47–55.

Dallimer, M., Tang, Z., Bibby, P. R., Brindley, P., Gaston, K. J., & Davies, Z. G. (2011). Temporal changes in greenspace in a highly urbanized region. *Biology Letters*, **7**(5), 763–766.

Dark, S. J., & Bram, D. (2007). The modifiable areal unit problem (MAUP) in physical geography. *Progress in Physical Geography*, **31**(5), 471–479.

Davies, Z. G., Fuller, R. A., Loram, A., Irvine, K. N., Sims, V., & Gaston, K. J. (2009). A national scale inventory of resource provision for biodiversity within domestic gardens. *Biological Conservation*, **142**(4), 761–771.

de Bell, S., Graham, H., Jarvis, S., & White, P. (2017). The importance of nature in mediating social and psychological benefits associated with visits to freshwater blue space. *Landscape and Urban Planning*, **167**, 118–127.

de Bell, S., Graham, H., & White, P. C. L. (2020a). Evaluating dual ecological and well-being benefits from an urban restoration project. *Sustainability*, **12**(2), 1–28.

de Bell, S., White, M., Griffiths, A., … Lovell, R. (2020b). Spending time in the garden is positively associated with health and wellbeing: Results from a national survey in England. *Landscape and Urban Planning*, **200**, 103836.

de Keijzer, C., Tonne, C., Sabia, S., … Dadvand, P. (2019). Green and blue spaces and physical functioning in older adults: Longitudinal analyses of the Whitehall II study. *Environment International*, **122**, 346–356.

de Vries, S., & Snep, R. (2019). Biodiversity in the Context of 'Biodiversity – Mental Health' Research. In *Biodiversity and Health in the Face of Climate Change*, Cham: Springer, pp. 159–173.

de Vries, S., ten Have, M., van Dorsselaer, S., van Wezep, M., Hermans, T., & de Graaf, R. (2016). Local availability of green and blue space and prevalence of common mental disorders in the Netherlands. *BJPsych Open*, **2**(6), 366–372.

de Vries, S., van Dillen, S. M. E., Groenewegen, P. P., & Spreeuwenberg, P. (2013). Streetscape greenery and health: Stress, social cohesion and physical activity as mediators. *Social Science and Medicine*, **94**, 26–33.

de Vries, S., Verheij, R. A., Groenewegen, P. P., & Spreeuwenberg, P. (2003). Natural environments - Healthy environments? An exploratory analysis of the relationship between greenspace and health. *Environment and Planning A*, **35**(10), 1717–1731.

Defra. (2011). *The Natural Choice: securing the value of nature*. *English*. Retrieved from http://www.official-documents.gov.uk/document/cm80/8082/8082.pdf

Defra. (2016). UK-AIR pollution-climate modelled data. Retrieved from https://uk-air.defra.gov.uk/data/pcm-data

Defra. (2017). *Evidence Statement on the links between natural environments and human health*, London. Retrieved from https://beyondgreenspace.net/2017/03/09/defra-evidence-statement-on-the-links-between-natural-environments-and-human-health/

Defra. (2018). Rural population 2014/15. Retrieved from https://www.gov.uk/government/publications/rural-population-and-migration/rural-population-201415. [Last accessed: 25th July 2020].

Dennis, E. B., Morgan, B. J. T., Roy, D. B., & Brereton, T. M. (2017). Urban indicators for UK butterflies. *Ecological Indicators*, **76**, 184–193.

Dennis, M., & James, P. (2017). Evaluating the relative influence on population health of domestic gardens and green space along a rural-urban gradient. *Landscape and Urban Planning*, **157**, 343–351.

Department for Communities and Local Government. (2004). Indices of multiple deprivation 2004. Retrieved from http://webarchive.nationalarchives.gov.uk/20100410180038/http://www.communities.gov.uk/archived/general-content/communities/indicesofdeprivation/216309/

Department for Communities and Local Government. (2005). Generalised Land Use Database. Retrieved from https://data.gov.uk/dataset/land_use_statistics_generalised_land_use_database

Department for Communities and Local Government. (2007). Indices of multiple deprivation 2007. Retrieved from http://webarchive.nationalarchives.gov.uk/20100410180038/http://communities.gov.uk/communities/neighbourhoodrenewal/deprivation/deprivation07/

Department for Communities and Local Government. (2010). Indices of multiple deprivation 2010. Retrieved from https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010

Department for Communities and Local Government. (2015). *The English Indices of Deprivation 2015: Research Report*. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/464485/English_Indices_of_Deprivation_2015_-_Technical-Report.pdf. [Last accessed: 19th December 2019].

Department for Communities and Local Government. (2019). *National Planning Policy Framework*, London.

Department of Health. (2014). *Annual Report of the Chief Medical Officer 2013: Public Mental Health Priorities: Investing in the Evidence*. Retrieved from https://www.gov.uk/government/publications/chief-medical-officer-cmo-annual-report-public-mental-health

Di Tella, R., & Macculloch, R. (2006). Some uses of happiness data in economics. *Journal of Economic Perspectives*, **20**(1), 25–46.

Di Tella, R., MacCulloch, R. J., & Oswald, A. J. (2003). The Macroeconomics of Happiness. *Review of Economics and Statistics*, **85**(4), 809–827.

Dibben, C., & Clemens, T. (2015). Place of work and residential exposure to ambient air pollution and birth outcomes in Scotland, using geographically fine pollution climate mapping estimates. *Environmental Research*, **140**, 535–541.

Diener, E., Inglehart, R., & Tay, L. (2013). Theory and Validity of Life Satisfaction Scales. *Social Indicators Research*, **112**(3), 497–527.

Diener, E., Lucas, R., & Oishi, S. (2002). Subjective well-being. *Handbook of Positive Psychology*.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: three decades of progress. *Psychological Bulletin*, **125**(2), 276–302.

Dolan, P., & Metcalfe, R. (2012). Measuring Subjective Wellbeing: Recommendations on Measures for use by National Governments. *Journal of Social Policy*, **41**(02), 409–427.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, **29**(1), 94–122.

Donovan, N., & Halpern, D. (2002). *Life satisfaction: The state of knowledge and implications for government. Cabinet Office analytical paper, December 2002. London: Cabinet Office*.

Douglas, O., Lennon, M., & Scott, M. (2017). Green space benefits for health and well-being: A life-course approach for urban planning, design and management. *Cities*, **66**, 53–62.

Du, G., Shin, K. J., & Managi, S. (2018). Variability in impact of air pollution on subjective well-being. *Atmospheric Environment*, **183**, 175–208.

Dye, C. (2008). Health and urban living. *Science*, **319**(5864), 766–769.

Dzhambov, A. M., Browning, M. H. E. M., Markevych, I., Hartig, T., & Lercher, P. (2020). Analytical approaches to testing pathways linking greenspace to health: A scoping review of the empirical literature. *Environmental Research*, **186**, 109613.

Dzhambov, A. M., Markevych, I., Hartig, T., … Dimitrova, D. D. (2018). Multiple pathways link urban green- and bluespace to mental health in young adults. *Environmental Research*, **166**, 223–233.

Egan, K. J., Corrigan, J. R., & Dwyer, D. F. (2015). Three reasons to use annual payments in contingent valuation surveys: Convergent validity, discount rates, and mental accounting. *Journal of Environmental Economics and Management*, **72**(2006), 123–136.

Egorov, A. I., Griffin, S. M., Converse, R. R., … Wade, T. J. (2017). Vegetated land cover near residence is associated with reduced allostatic load and improved biomarkers of neuroendocrine, metabolic and immune functions. *Environmental Research*, **158**, 508–521.

Ekkel, E. D., & de Vries, S. (2017). Nearby green space and human health: Evaluating accessibility metrics. *Landscape and Urban Planning*, **157**, 214–220.

Elliott, L. R., White, M. P., Grellier, J., … Fleming, L. E. (2020). Landscape and Urban Planning

Research Note : Residential distance and recreational visits to coastal and inland blue spaces in eighteen countries. *Landscape and Urban Planning*, **198**, 103800.

Elliott, L. R., White, M. P., Grellier, J., Rees, S. E., Waters, R. D., & Fleming, L. E. (2018). Recreational visits to marine and coastal environments in England: Where, what, who, why, and when? *Marine Policy*, **97**(February), 305–314.

Engemann, K., Pedersen, C. B., Arge, L., Tsirogiannis, C., Mortensen, P. B., & Svenning, J.-C. (2019). Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. *Proceedings of the National Academy of Sciences*, **116**(11), 5188–5193.

Environment Agency. (2020). *The state of the environment: health, people and the environment*. Retrieved from https://www.gov.uk/government/publications/state-of-the-environment

ESRI. (2011). ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

ESRI. (2015). ArcGIS Desktop: Release 10.3.1. Redlands, CA: Environmental Systems Research Institute.

ESRI. (2018). ArcGIS Desktop: Release 10.6. Redlands, CA: Environmental Systems Research Institute.

European Commission. (2019). Air Quality - Existing Legislation. Retrieved from https://ec.europa.eu/environment/air/quality/existing_leg.htm

European Environment Agency. (2017). Air pollution definition. Retrieved from https://www.eea.europa.eu/help/glossary/eea-glossary/air-pollution. [Last accessed: 19th July 2020].

European Environment Agency. (2018). *Europe's urban air quality — re-assessing implementation challenges in cities*. *EEA Report No 24/2018*. Retrieved from https://www.eea.europa.eu/publications/europes-urban-air-quality

Fan, Y., Das, K. V., & Chen, Q. (2011). Neighborhood green, social support, physical activity, and stress: Assessing the cumulative impact. *Health and Place*, **17**(6), 1202–1211.

Feddersen, J., Metcalfe, R., & Wooden, M. (2016). Subjective wellbeing : why weather matters. *Journal of the Royal Statistical Society A.*, **179**(1), 203–228.

Feldman, F. (2019). An improved whole life satisfaction theory of happiness? *International Journal of Wellbeing*, **9**(2), 1–7.

Felsten, G. (2009). Where to take a study break on the college campus: An attention restoration theory perspective. *Journal of Environmental Psychology*, **29**(1), 160–167.

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.

Ferreira, S., Akay, A., Brereton, F., … Ningal, T. F. (2013). Life satisfaction and air quality in Europe. *Ecological Economics*, **88**, 1–10.

Ferreira, S., & Moro, M. (2010). On the use of subjective well-being data for environmental valuation. *Environmental and Resource Economics*, **46**(3), 249–273.

Ferrer-i-Carbonell, A., & Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, **114**(1997), 641–659.

Fields in Trust. (2018). *Revaluing parks and green spaces: Measuring their economic and wellbeing value to individuals*, London. Retrieved from www.fieldsintrust.org

Fields in Trust. (2019). Nature in parks: Greenspaces on former industrial land providing a platform for nature. Retrieved from http://www.fieldsintrust.org/News/green-spaces-on-former-industrial-land-providing-a-platform-for-nature. [Last accessed: 9th September 2020].

Fields in Trust. (2020). Green Space Index. Retrieved from http://www.fieldsintrust.org/green-space-index. [Last accessed: 16th September 2020].

Finlay, J., Franke, T., McKay, H., & Sims-Gould, J. (2015). Therapeutic landscapes and wellbeing in later life: Impacts of blue and green spaces for older adults. *Health and Place*, **34**, 97–106.

Foley, R., & Kistemann, T. (2015). Blue space geographies: Enabling health in place. *Health and Place*, **35**, 157–165.

Forgeard, M. J. C., Jayawickreme, E., Kern, M. L., & Seligman, M. E. P. (2011). Doing the Right Thing: Measuring Well-Being for Public Policy. *International Journal of Wellbeing*, **1**(1), 79–106.

Forrest, R., & Kearns, a. (2001). Social cohesion, social capital and the neighbourhood, **38**(12), 2125–2143.

Francis, J., Wood, L. J., Knuiman, M., & Giles-Corti, B. (2012). Quality or quantity? Exploring the relationship between Public Open Space attributes and mental health in Perth, Western Australia. *Social Science and Medicine*, **74**(10), 1570–1577.

Frey, B. S., Luechinger, S., & Stutzer, A. (2010). The Life Satisfaction Approach to Environmental Valuation. *Annual Review of Resource Economics*, **2**, 139–160.

Fuller, R. A., & Gaston, K. J. (2009). The scaling of green space coverage in European cities. *Biology Letters*, **5**(3), 352–355.

Fuller, R. A., Irvine, K. N., Devine-Wright, P., Warren, P. H., & Gaston, K. J. (2007). Psychological benefits of greenspace increase with biodiversity. *Biology Letters*, **3**(4), 390–4.

Garrett, J. K., Clitherow, T. J., White, M. P., Wheeler, B. W., & Fleming, L. E. (2019a). Coastal proximity and mental health among urban adults in England: The moderating effect of household income. *Health and Place*, **59**, 102200.

Garrett, J. K., White, M. P., Huang, J., … Wong, M. C. S. (2019b). Urban blue space and health and wellbeing in Hong Kong: Results from a survey of older adults. *Health and Place*, **55**, 100–110.

Gascon, M., Mas, M. T., Martínez, D., … Nieuwenhuijsen, M. J. (2015). Mental health benefits of long-term exposure to residential green and blue spaces: A systematic review. *International Journal of Environmental Research and Public Health*, **12**(4), 4354–4379.

Gascon, M., Sánchez-Benavides, G., Dadvand, P., … Nieuwenhuijsen, M. (2018). Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study. *Environmental Research*, **162**, 231–239.

Gascon, M., Zijlema, W., Vert, C., White, M. P., & Nieuwenhuijsen, M. J. (2017). Outdoor blue spaces, human health and well-being: A systematic review of quantitative studies. *International Journal of Hygiene and Environmental Health*, **220**(8), 1207–1221.

Gibbons, S., Mourato, S., & Resende, G. M. (2014). The Amenity Value of English Nature: A Hedonic Price Approach. *Environmental and Resource Economics*, **57**(2), 175–196.

Giles-Corti, B., Knuiman, M., Timperio, A., … Bulsara, M. (2008). Evaluation of the implementation of a state government community design policy aimed at increasing local walking: Design issues and baseline results from RESIDE, Perth Western Australia. *Preventive Medicine*, **46**(1), 46–54.

Gould, W. (2000). Remote sensing of vegetation, plant species richness, and regional biodiversity hotspots. *Ecological Applications*, **10**(6), 1861–1870.

Grahn, P., & Stigsdotter, U. A. (2003). Landscape planning and stress. *Urban Forestry & Urban Greening*, **2**, 1–18.

Greater London Authority. (2016). *The London Plan: The Spatial Development Strategy For London Consolidated With Alterations Since 2011*. Retrieved from WWW.LONDON.GOV.UK/WHAT-WE-DO/PLANNING/LONDON-PLAN/CUR- RENT-LONDON-PLAN%0ANote:

Greenspace Information for Greater London CIC. (2017). Data Guide Appendix C. Retrieved from https://www.gigl.org.uk/giglpolicy/data-guide/

Greenspace Information for Greater London CIC. (2019a). Areas of Deficiency in Access to Nature. Retrieved from https://www.gigl.org.uk/designated-sites/areas-of-deficiency-in-access-to-nature/. [Last accessed: 20th September 2020].

Greenspace Information for Greater London CIC. (2019b). Open Spaces. Retrieved from https://www.gigl.org.uk/open-spaces/. [Last accessed: 20th September 2020].

Haaland, C., & van den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban Forestry and Urban Greening*, **14**(4), 760–771.

Hand, C. (2020). Spatial influences on domains of life satisfaction in the UK. *Regional Studies*, **54**(6), 802–813.

Hartig, T., Evans, G. W., Jamner, L. D., Davis, D. S., & Gärling, T. (2003). Tracking restoration in natural and urban field settings. *Journal of Environmental Psychology*, **23**, 109–123.

Hartig, T., Mitchell, R., de Vries, S., & Frumkin, H. (2014). Nature and Health. *Annual Review* *of Public Health*, **35**(1), 207–228.

Helliwell, J. F. (2006). Well-Being, Social Capital and Public Policy: What's New?*. *The Economic Journal*, **116**(510), C34–C45.

Helliwell, J., Layard, R., Sachs, J. D., & Neve, J. De. (2020). *World Happiness Report 2020*, New York: Sustainable Development Solutions Network.

Hidaka, B. H. (2012). Depression as a disease of modernity: Explanations for increasing prevalence. *Journal of Affective Disorders*, **140**(3), 205–214.

Higgs, G., & Langford, M. (2009). GIScience, environmental justice, & estimating populations at risk: The case of landfills in Wales. *Applied Geography*, **29**(1), 63–76.

Hirschauer, N., Lehberger, M., & Musshoff, O. (2015). Happiness and Utility in Economic Thought-Or: What Can We Learn from Happiness Research for Public Policy Analysis and Public Policy Making? *Social Indicators Research*, **121**, 647–674.

HM Government. (2018). *A Green Future: Our 25 Year Plan to Improve the Environment*, London, UK. Retrieved from www.gov.uk/government/publications.

Hough, R. L. (2014). Biodiversity and human health: Evidence for causality? *Biodiversity and Conservation*, **23**(2), 267–288.

Houlden, V., João de Albuquerque, P., Weich, S., & Jarvis, S. (2019a). Does nature make us happier? A spatial error model of greenspace types and mental wellbeing. *Environment and Planning B: Urban Analytics and City Science*, **0**(0), 1–16.

Houlden, V., Porto de Albuquerque, J., Weich, S., & Jarvis, S. (2019b). A spatial analysis of proximate greenspace and mental wellbeing in London. *Applied Geography*, **109**, 102036.

Houlden, V., Weich, S., de Albuquerque, J. P., Jarvis, S., & Rees, K. (2018). The relationship between greenspace and the mental wellbeing of adults: A systematic review. *PloS ONE*, **13**(9), 1–35.

Houlden, V., Weich, S., & Jarvis, S. (2017). A cross-sectional analysis of green space prevalence and mental wellbeing in England. *BMC Public Health*, **17**, 1–9.

Hoyle, H., Jorgensen, A., & Hitchmough, J. D. (2019). What determines how we see nature? Perceptions of naturalness in designed urban green spaces. *People and Nature*, **1**(2), 167–180.

Hswen, Y., Qin, Q., Brownstein, J. S., & Hawkins, J. B. (2019). Feasibility of using social media to monitor outdoor air pollution in London, England. *Preventive Medicine*, **121**, 86–93.

Huber, M., André Knottnerus, J., Green, L., … Smid, H. (2011). How should we define health? *BMJ (Online)*, **343**(7817), 1–3.

Hunter, A. J., & Luck, G. W. (2015). Defining and measuring the social-ecological quality of urban greenspace: a semi-systematic review. *Urban Ecosystems*, **18**(4), 1139–1163.

Hunter, R. F., Cleland, C., Cleary, A., … Braubach, M. (2019). Environmental, health, wellbeing, social and equity effects of urban green space interventions: A meta-narrative evidence synthesis. *Environment International*, **130**, 104923.

Husk, K., Blockley, K., Lovell, R., … Garside, R. (2020). What approaches to social prescribing work, for whom, and in what circumstances? A realist review. *Health and Social Care in the Community*, **28**(2), 309–324.

Hyder, K., Townhill, B., Anderson, L. G., Delany, J., & Pinnegar, J. K. (2015). Can citizen science contribute to the evidence-base that underpins marine policy? *Marine Policy*, **59**, 112–120.

Institute of Economic Affairs. (2012). ...*and the Pursuit of Happiness*. (P. Booth, Ed.), London. doi:10.1037/000370

Isaac, N. J. B., & Pocock, M. J. O. (2015). Bias and information in biological records. *Biological Journal of the Linnean Society*, **115**(3), 522–531.

Jansson, M., Fors, H., Lindgren, T., & Wiström, B. (2013). Perceived personal safety in relation to urban woodland vegetation - A review. *Urban Forestry and Urban Greening*, **12**(2), 127–133.

Jarvis, I., Gergel, S., Koehoorn, M., & van den Bosch, M. (2020a). Greenspace access does not correspond to nature exposure: Measures of urban natural space with implications for health research. *Landscape and Urban Planning*, **194**, 103686.

Jarvis, I., Koehoorn, M., Gergel, S. E., & van den Bosch, M. (2020b). Different types of urban natural environments influence various dimensions of self-reported health. *Environmental Research*, **186**, 109614.

Jeanjean, A. P. R., Monks, P. S., & Leigh, R. J. (2016). Modelling the effectiveness of urban trees and grass on PM2.5 reduction via dispersion and deposition at a city scale. *Atmospheric Environment*, **147**, 1–10.

Jennings, V., Floyd, M. F., Shanahan, D., Coutts, C., & Sinykin, A. (2017). Emerging issues in urban ecology: implications for research, social justice, human health, and well-being. *Population and Environment*, **39**(1), 69–86.

JNCC. (2008). Habitat correspondences spreadsheet. Retrieved September 18, 2020, from https://hub.jncc.gov.uk/assets/9e70531b-5467-4136-88f6-3b3dd905b56d

Jones, B. A. (2017). Invasive Species Impacts on Human Well-being Using the Life Satisfaction Index. *Ecological Economics*, **134**, 250–257.

Kabisch, N. (2015). Ecosystem service implementation and governance challenges in urban green space planning-The case of Berlin, Germany. *Land Use Policy*, **42**, 557–567.

Kahneman, D., & Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *Journal of Economic Perspectives*, **20**(1), 3–24.

Kahneman, D., & Sugden, R. (2005). Experienced utility as a standard of policy evaluation. *Environmental and Resource Economics*, **32**(1), 161–181.

Kaplan, R. (2001). The nature of the view from home psychological benefits. *Environment and Behavior*, **33**(4), 507–542.

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*, New York: Cambridge University Press.

Kaplan, S. (1995). The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, **15**(1995), 169–182.

Kellert, S. R., & Wilson, E. O. (1993). *The Biophilia Hypothesis*. *Frontiers in Ecology and the Environment*, Vol. 5. Retrieved from http://www.amazon.com/Biophilia-Hypothesis-Shearwater-Book/dp/1559631473

Keniger, L. E., Gaston, K. J., Irvine, K. N., & Fuller, R. A. (2013). What are the benefits of interacting with nature? *International Journal of Environmental Research and Public Health*, **10**(3), 913–935.

Kenter, J. O. (2016). Shared, plural and cultural values. *Ecosystem Services*, **21**, 175–183.

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management*, **45**(1), 24–39.

King, M. F., Renó, V. F., & Novo, E. M. L. M. (2014). The Concept, Dimensions and Methods of Assessment of Human Well-Being within a Socioecological Context: A Literature Review. *Social Indicators Research*, **116**, 681–698.

Klompmaker, J. O., Hoek, G., Bloemsma, L. D., … Janssen, N. A. H. (2018). Green space definition affects associations of green space with overweight and physical activity. *Environmental Research*, **160**, 531–540.

Klompmaker, J. O., Janssen, N. A. H., Bloemsma, L. D., … Hoek, G. (2019). Associations of combined exposures to surrounding green, air pollution, and road traffic noise with cardiometabolic diseases. *Environmental Health Perspectives*, **127**(8), 1–15.

Kondo, M. C., Fluehr, J. M., McKeon, T., & Branas, C. C. (2018). Urban green space and its impact on human health. *International Journal of Environmental Research and Public Health*, **15**, 1–28.

Kondo, M. C., Triguero-Mas, M., Donaire-Gonzalez, D., … Nieuwenhuijsen, M. J. (2020). Momentary mood response to natural outdoor environments in four European cities. *Environment International*, **134**, 105237.

Krekel, C., Kolbe, J., & Wüstemann, H. (2016). The greener, the happier? The effect of urban land use on residential well-being. *Ecological Economics*, **121**, 117–127.

Krekel, C., & MacKerron, G. (2020). How environmental quality affects our happiness. In J. D. Helliwell, John F., Layard, Richard and Sachs, ed., *World Happiness Report 2020. World Happiness Report (2020).*, Sustainable Development Solutions Network, New York, USA, pp. 95–112.

Krueger, A. B., & Schkade, D. a. (2008). The Reliability of Subjective Well-Being Measures. *Journal of Public Economics*, **92**(8–9), 1833–1845.

Kruize, H., van Kamp, I., van den Berg, M., … Nieuwenhuijsen, M. (2020). Exploring mechanisms underlying the relationship between the natural outdoor environment and health and well-being – Results from the PHENOTYPE project. *Environment International*, **134**, 105173.

Kuminoff, N. V., Parmeter, C. F., & Pope, J. C. (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? *Journal of Environmental Economics and Management*, **60**(3), 145–160.

Labib, S. M., Lindley, S., & Huck, J. J. (2020a). Scale effects in remotely sensed greenspace metrics and how to mitigate them for environmental health exposure assessment. *Computers, Environment and Urban Systems*, **82**, 101501.

Labib, S. M., Lindley, S., & Huck, J. J. (2020b). Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. *Environmental Research*, **180**, 1–22.

Lachowycz, K., & Jones, A. P. (2011). Greenspace and obesity: A systematic review of the evidence. *Obesity Reviews*, **12**(5), 183–189.

Laffan, K. (2018). Every breath you take, every move you make: Visits to the outdoors and physical activity help to explain the relationship between air pollution and subjective wellbeing. *Ecological Economics*, **147**, 96–113.

Lai, H., Flies, E. J., Weinstein, P., & Woodward, A. (2019). The impact of green space and biodiversity on health. *Frontiers in Ecology and the Environment*, 1–8.

Lapointe, M., Gurney, G. G., & Cumming, G. S. (2020). Urbanization alters ecosystem service preferences in a Small Island Developing State. *Ecosystem Services*, **43**, 101109.

Laumann, K., Gärling, T., & Stormark, K. M. (2003). Selective attention and heart rate responses to natural and urban environments. *Journal of Environmental Psychology*, **23**, 125–134.

Layard, R. (2005). *Happiness: Lessons from a new science*, The Penguin Press.

Lederbogen, F., Kirsch, P., Haddad, L., … Meyer-Lindenberg, A. (2011). City living and urban upbringing affect neural social stress processing in humans. *Nature*, **474**, 498–501.

Leong, M., Dunn, R. R., & Trautwein, M. D. (2018). Biodiversity and socioeconomics in the city: a review of the luxury effect. *Biology Letters*, **14**, 1–12.

Levin, N., Shmida, A., Levanoni, O., Tamari, H., & Kark, S. (2007). Predicting mountain plant richness and rarity from space using satellite-derived vegetation indices. *Diversity and Distributions*, **13**(6), 692–703.

Levinson, A. (2012). Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics*, **96**, 869–880.

Lindemann-Matthies, P., & Matthies, D. (2018). The influence of plant species richness on stress recovery of humans. *Web Ecology*, **18**(2), 121–128.

London Wildlife Trust. (2015). *Spaces wild; championing the values of London's wildlife sites*. Retrieved from https://www.wildlondon.org.uk/about/research-and-reports

Lorenc, T., Petticrew, M., Whitehead, M., … Renton, A. (2013). Fear of crime and the environment: systematic review of UK qualitative evidence. *BMC Public Health*, **13**(1), 496.

Lovell, R. (2018). *Demystifying Health, Valuing Nature Paper, VNP13*.

Lovell, R., Wheeler, B. W., Higgins, S. L., Irvine, K. N., & Depledge, M. H. (2014). A systematic review of the health and well-being benefits of biodiverse environments. *Journal of Toxicology and Environmental Health. Part B, Critical Reviews*, **17**(1), 1–20.

Luck, G. W., Davidson, P., Boxall, D., & Smallbone, L. (2011). Relations between Urban Bird and Plant Communities and Human Well-Being and Connection to Nature. *Conservation Biology*, **25**(4), 816–826.

Luechinger, S. (2009). Valuing air quality using the life satisfaction approach. *Economic Journal*, **119**, 482–515.

Luechinger, S. (2010). Life satisfaction and transboundary air pollution. *Economics Letters*, **107**(1), 4–6.

Luechinger, S., & Raschky, P. A. (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics*, **93**(3–4), 620–633.

Lusk, J. L., & Norwood, F. B. (2009). An Inferred Valuation Method. *Land Economics*, **85**(3), 500–514.

Lynn, P., & Borkowska, M. (2018). *Some Indicators of Sample Representativeness and Attrition Bias for BHPS and Understanding Society* (No. 01), Colchester.

Maas, J., van Dillen, S. M. E., Verheij, R. A., & Groenewegen, P. P. (2009a). Social contacts as a possible mechanism behind the relation between green space and health. *Health and Place*, **15**(2), 586–595.

Maas, J., Verheij, R. A., De Vries, S., Spreeuwenberg, P., Schellevis, F. G., & Groenewegen, P. P. (2009b). Morbidity is related to a green living environment. *Journal of Epidemiology and Community Health*, **63**(12), 967–973.

Maas, J., Verheij, R. a, Groenewegen, P. P., de Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: how strong is the relation? *Journal of Epidemiology and Community Health*, **60**, 587–592.

Mace, G. M., Barrett, M., Burgess, N. D., … Purvis, A. (2018). Aiming Higher - Bending the Curve of Biodiversity Loss. *Nature Sustainability*, **1**, 448–451.

Mackerron, G., & Mourato, S. (2008). Life satisfaction and air quality in London. *Ecological Economics*, **68**(5), 1441–1453.

MacKerron, G., & Mourato, S. (2013). Happiness is greater in natural environments. *Global Environmental Change*, **23**(5), 992–1000.

Maddison, D., & Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics*, **70**(12), 2437–2445.

Markevych, I., Schoierer, J., Hartig, T., … Fuertes, E. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research*, **158**, 301–317.

Marselle, M. R. (2019). Theoretical foundations of biodiversity and mental health relationships. In *Biodiversity and Health in the Face of Climate Change*, Cham: Springer, pp. 133–158.

Marselle, M. R., Irvine, K. N., Lorenzo-Arribas, A., & Warber, S. L. (2015). Moving beyond green: Exploring the relationship of environment type and indicators of perceived environmental quality on emotional well-being following group walks. *International Journal of Environmental Research and Public Health*, **12**(1), 106–130.

Marselle, M. R., Irvine, K. N., Lorenzo-Arribas, A., & Warber, S. L. (2016). Does perceived restorativeness mediate the effects of perceived biodiversity and perceived naturalness on emotional well-being following group walks in nature? *Journal of Environmental Psychology*, **46**, 217–232.

Marselle, M. R., Martens, D., Dallimer, M., & Irvine, K. N. (2019). Review of the Mental Health and Well-being Benefits of Biodiversity. In *Biodiversity and Health in the Face of Climate*

Change, Cham: Springer, pp. 174–211.

Martin, L., White, M. P., Hunt, A., Richardson, M., Pahl, S., & Burt, J. (2020). Nature contact, nature connectedness and associations with health, wellbeing and pro-environmental behaviours. *Journal of Environmental Psychology*, **68**, 1–12.

Mavoa, S., Davern, M., Breed, M., & Hahs, A. (2019a). Higher levels of greenness and biodiversity associate with greater subjective wellbeing in adults living in Melbourne, Australia. *Health & Place*, **57**, 321–329.

Mavoa, S., Lucassen, M., Denny, S., Utter, J., Clark, T., & Smith, M. (2019b). Natural neighbourhood environments and the emotional health of urban New Zealand adolescents. *Landscape and Urban Planning*, **191**(July), 103638.

Mayor of London. (2020). *London Green Spaces Commission report*.

McDonald, a. G., Bealey, W. J., Fowler, D., … Nemitz, E. (2007). Quantifying the effect of urban tree planting on concentrations and depositions of PM10 in two UK conurbations. *Atmospheric Environment*, **41**(38), 8455–8467.

McFadden, D. (1999). Rationality for economists? *Journal of Risk and Uncertainty*, **19**(1–3), 73–105.

McGinlay, J., Parsons, D. J., Morris, J., … Bullock, J. M. (2017). Do charismatic species groups generate more cultural ecosystem service benefits? *Ecosystem Services*, **27**, 15–24.

McKinley, D. C., Miller-Rushing, A. J., Ballard, H. L., … Soukup, M. A. (2018). Citizen science can improve conservation science, natural resource management, and environmental protection. In *Advances in Ecological Research*, Vol. 59, Elsevier Ltd, pp. 169–223.

McMahan, E. A., & Estes, D. (2015). The effect of contact with natural environments on positive and negative affect: A meta-analysis. *Journal of Positive Psychology*, **10**(6), 507–519.

Mears, M., Brindley, P., Jorgensen, A., Ersoy, E., & Maheswaran, R. (2019a). Greenspace spatial characteristics and human health in an urban environment: An epidemiological study using landscape metrics in Sheffield, UK. *Ecological Indicators*, **106**, 105464.

Mears, M., Brindley, P., Maheswaran, R., & Jorgensen, A. (2019b). Understanding the socioeconomic equity of publicly accessible greenspace distribution: The example of

Sheffield, UK. *Geoforum*, **103**, 126–137.

Mennis, J., Mason, M., & Ambrus, A. (2018). Urban greenspace is associated with reduced psychological stress among adolescents: A Geographic Ecological Momentary Assessment (GEMA) analysis of activity space. *Landscape and Urban Planning*, **174**, 1–9.

Mental Health Foundation. (2016). *Fundamental facts about mental health 2016*, London. Retrieved from https://www.mentalhealth.org.uk/sites/default/files/fundamental-facts-about-mental-health-2016.pdf

Millennium Ecosystem Assessment. (2005). *Ecosystems and Human Well-being: Synthesis. Island Press*, Washington, DC.

Milligan, C., & Bingley, A. (2007a). Restorative places or scary spaces? The impact of woodland on the mental well-being of young adults. *Health and Place*, **13**(4), 799–811.

Milligan, C., & Bingley, A. (2007b). Restorative places or scary spaces? The impact of woodland on the mental well-being of young adults. *Health and Place*, **13**(4), 799–811.

Milligan, C., Gatrell, A., & Bingley, A. (2004). “Cultivating health”: Therapeutic landscapes and older people in northern England. *Social Science and Medicine*, **58**(9), 1781–1793.

Miret, M., Caballero, F. F., Olaya, B., … Ayuso-Mateos, J. L. (2017). Association of experienced and evaluative well-being with health in nine countries with different income levels: A cross-sectional study. *Globalization and Health*, **13**(1), 1–11.

Mitchell, R. (2013). Is physical activity in natural environments better for mental health than physical activity in other environments? *Social Science and Medicine*, **91**, 130–134.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: an observational population study. *Lancet*, **372**, 1655–1660.

Mizen, A., Fry, R., Grinnell, D., & E. Rodgers, S. (2015). Quantifying the Error Associated with Alternative GIS-based Techniques to Measure Access to Health Care Services. *AIMS Public Health*, **2**(4), 746–761.

Morckel, V. (2015). Community gardens or vacant lots? Rethinking the attractiveness and seasonality of green land uses in distressed neighborhoods. *Urban Forestry and Urban Greening*, **14**(3), 714–721.

Morgenstern, H., & Thomas, D. (1993). Principles of study design in environmental epidemiology. *Environmental Health Perspectives*, **101**(SUPPL. 4), 23–38.

Murphy, J. J., Allen, P. G., Stevens, T. H., & Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, **30**(3), 313–325.

Nandi, A., & Platt, L. (2017). Are there differences in responses to social identity questions in face-to-face versus telephone interviews? Results of an experiment on a longitudinal survey. *International Journal of Social Research Methodology*, **20**(2), 151–166.

Nath, T. K., Zhe Han, S. S., & Lechner, A. M. (2018). Urban green space and well-being in Kuala Lumpur, Malaysia. *Urban Forestry and Urban Greening*, **36**, 34–41.

Natural Capital Coalition. (2020). Natural Capital. Retrieved from https://naturalcapitalcoalition.org/natural-capital-2/

Natural England. (2008). *Understanding the Relevance and Application of the Access to Natural Green Space Standard*. Retrieved from http://publications.naturalengland.org.uk/publication/5081534874779648?category=47004. [Last accessed: 30th September 2020].

Natural England. (2009). *An estimate of the economic and health value and cost effectiveness of the expanded WHI scheme 2009. Natural England Technical Information Note TIN055*, Peterborough.

Natural England. (2010). *Nature Nearby: Accessible Natural Greenspace Guidance*, Peterborough.

Natural England. (2013). *Monitor of Engagement with the Natural Environment: The national survey on people and the natural environment. Annual Report from the 2011-2012 Survey*. Retrieved from http://publications.naturalengland.org.uk/publication/1712385

Navarrete-Hernandez, P., & Laffan, K. (2019). A greener urban environment: Designing green infrastructure interventions to promote citizens' subjective wellbeing. *Landscape and Urban Planning*, **191**, 103618.

Neuteleers, S., & Engelen, B. (2015). Talking money: How market-based valuation can undermine environmental protection. *Ecological Economics*, **117**, 253–260.

Nielsen, T. S., & Hansen, K. B. (2007). Do green areas affect health? Results from a Danish survey on the use of green areas and health indicators. *Health and Place*, **13**(4), 839–850.

Nieuwenhuijsen, M. J., Khreis, H., Triguero-Mas, M., Gascon, M., & Dadvand, P. (2017). Fifty shades of green. *Epidemiology*, **28**(1), 63–71.

Nisbet, E. K., Zelenski, J. M., & Murphy, S. a. (2010). Happiness is in our Nature: Exploring Nature Relatedness as a Contributor to Subjective Well-Being. *Journal of Happiness Studies*, **12**(2), 303–322.

Nowak, D. J., Hirabayashi, S., Bodine, A., & Greenfield, E. (2014). Tree and forest effects on air quality and human health in the United States. *Environmental Pollution*, **193**, 119–129.

Nuckols, J. R., Ward, M. H., & Jarup, L. (2004). Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environmental Health Perspectives*, **112**, 1007–1015.

Nutsford, D., Pearson, A. L., Kingham, S., & Reitsma, F. (2016). Residential exposure to visible blue space (but not green space) associated with lower psychological distress in a capital city. *Health and Place*, **39**, 70–78.

O'Brien, L., Morris, J., & Stewart, A. (2014). Engaging with peri-urban woodlands in england: The contribution to people's health and well-being and implications for future management. *International Journal of Environmental Research and Public Health*, **11**(6), 6171–6192.

OECD. (2013). *OECD Guidelines on Measuring Subjective Well-being*. *OECD Publishing, Paris. DOI: http://dx.doi.org/10.1787/9789264191655-en*. Retrieved from http://www.oecd-ilibrary.org/economics/oecd-guidelines-on-measuring-subjective-well-being_9789264191655-en

OECD. (2018). *Health at a Glance: Europe 2018: State of Health in the EU Cycle*, Paris.

Office for National Statistics. (2016). Lower super output area mid-year population estimates, census 2001 LSOAs. Retrieved from https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates

Office for National Statistics. (2020a). Estimates of population for the UK, England and Wales, Scotland, and Northern Ireland. Retrieved August 2, 2020, from https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland

Office for National Statistics. (2020b). One in eight British households has no garden. Retrieved from https://www.ons.gov.uk/economy/environmentalaccounts/articles/oneineightbritishhouseholdshasnogarden/2020-05-14. [Last accessed: 15th September 2020].

Office of the Deputy Prime Minister. (2002). *Planning Policy Guidance 17: Planning for open space, sport and recreation.*, Office of the Deputy Prime Minister, London [online]. Retrieved from https://webarchive.nationalarchives.gov.uk/20120920042539/http://www.communities.gov.uk/documents/planningandbuilding/pdf/ppg17.pdf. [Last accessed: 5th September 2019].

Ohly, H., White, M. P., Wheeler, B. W., … Garside, R. (2016). Attention Restoration Theory: A systematic review of the attention restoration potential of exposure to natural environments. *Journal of Toxicology and Environmental Health - Part B: Critical Reviews*, **19**(7), 305–343.

Oindo, B. O., & Skidmore, A. K. (2002). Interannual variability of NDVI and species richness in Kenya. *International Journal of Remote Sensing*, **23**(2), 285–298.

Ojala, A., Korpela, K., Tyrväinen, L., Tiittanen, P., & Lanki, T. (2019). Restorative effects of urban green environments and the role of urban-nature orientedness and noise sensitivity: A field experiment. *Health and Place*, **55**, 59–70.

Olsen, J. R., Nicholls, N., & Mitchell, R. (2019). Are urban landscapes associated with reported life satisfaction and inequalities in life satisfaction at the city level? A cross-sectional study of 66 European cities. *Social Science and Medicine*, **226**, 263–274.

Orru, K., Orru, H., Maasikmets, M., Hendrikson, R., & Ainsaar, M. (2016). Well-being and environmental quality: Does pollution affect life satisfaction? *Quality of Life Research*, **25**(3), 699–705.

Park, J. J., O’Brien, L., Roe, J., Ward Thompson, C., & Mitchell, R. (2011). The natural outdoors and health: Assessing the value and potential contribution of secondary public data sets in the UK to current and future knowledge. *Health and Place*, **17**(1), 269–279.

Pasanen, T. P., White, M. P., Wheeler, B. W., Garrett, J. K., & Elliott, L. R. (2019). Neighbourhood blue space, health and wellbeing: The mediating role of different types of physical activity. *Environment International*, **131**, 105016.

Pascual, U., Balvanera, P., Díaz, S., … Yagi, N. (2017). Valuing nature's contributions to people: the IPBES approach. *Current Opinion in Environmental Sustainability*, **26**–**27**, 7–16.

Pearson, A. L., Pechal, J., Lin, Z., Benbow, M. E., Schmidt, C., & Mavoa, S. (2020). Associations detected between measures of neighborhood environmental conditions and human microbiome diversity. *Science of the Total Environment*, **745**, 141029.

Pearson, R. G. (2016). Reasons to Conserve Nature. *Trends in Ecology and Evolution*, **31**(5), 366–371.

Peen, J., Schoevers, R. a., Beekman, a. T., & Dekker, J. (2010). The current status of urban-rural differences in psychiatric disorders. *Acta Psychiatrica Scandinavica*, **121**(1), 84–93.

Pellissier, V., Schmucki, R., Pe'er, G., … Julliard, R. (2020). Effects of Natura 2000 on nontarget bird and butterfly species based on citizen science data. *Conservation Biology*, **34**(3), 666–676.

Pendleton, L., Atiyah, P., & Moorthy, A. (2007). Is the non-market literature adequate to support coastal and marine management? *Ocean and Coastal Management*, **50**(5–6), 363–378.

Pereira, G., Christian, H., Foster, S., … Giles-Corti, B. (2013). The association between neighborhood greenness and weight status: An observational study in Perth Western Australia. *Environmental Health: A Global Access Science Source*, **12**(1), 1–9.

Pereira, G., Foster, S., Martin, K., … Giles-Corti, B. (2012). The association between neighborhood greenness and cardiovascular disease: An observational study. *BMC Public Health*, **12**(1), 1.

Pett, T. J., Shwartz, A., Irvine, K. N., Dallimer, M., & Davies, Z. G. (2016). Unpacking the People–Biodiversity Paradox: A Conceptual Framework. *BioScience*, **66**(7), 576–583.

Pimm, S. L., Jenkins, C. N., Abell, R., … Sexton, J. O. (2014). The biodiversity of species and their rates of extinction, distribution, and protection. *Science*, **344**, 1246752.

Pocock, M. J. O., Chandler, M., Bonney, R., … Danielsen, F. (2018). A Vision for Global Biodiversity Monitoring With Citizen Science. In *Advances in Ecological Research*, 1st edn, Vol. 59, Elsevier Ltd., pp. 169–223.

Powdthavee, N. (2010). How much does money really matter? Estimating the causal effects of income on happiness. *Empirical Economics*, **39**(1), 77–92.

Power, M. C., Adar, S. D., Yanosky, J. D., & Weuve, J. (2016). NeuroToxicology Full length article Exposure to air pollution as a potential contributor to cognitive function , cognitive decline , brain imaging , and dementia : A systematic review of epidemiologic research. *Neurotoxicology*, **56**, 235–253.

Pretty, J., Peacock, J., Sellens, M., & Griffin, M. (2005). The mental and physical health outcomes of green exercise. *International Journal of Environmental Health Research*, **15**, 319–337.

Public Health England. (2018). *Estimation of costs to the NHS and social care due to the health impacts of air pollution: summary report About Public Health England*. Retrieved from https://www.gov.uk/government/publications/air-pollution-a-tool-to-estimate-healthcare-costs. [Last accessed: 25th July 2020].

Public Health England. (2020). Improving access to greenspace. A new review for 2020. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/904439/Improving_access_to_greenspace_2020_review.pdf

R Core Team. (2020). R: A Language and Environment for Statistical Computing, Vienna, Austria.

Raaschou-Nielsen, O., Andersen, Z. J., Beelen, R., … Hoek, G. (2013). Air pollution and lung cancer incidence in 17 European cohorts: prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *The Lancet Oncology*, **14**(9), 813–822.

Ramalho, C. E., & Hobbs, R. J. (2012). Time for a change: Dynamic urban ecology. *Trends in Ecology and Evolution*, **27**(3), 179–188.

Ratcliffe, E., Gatersleben, B., & Sowden, P. T. (2016). Associations with bird sounds: How do they relate to perceived restorative potential? *Journal of Environmental Psychology*, **47**, 136–144.

Ray, H., & Jakubec, S. L. (2014). Nature-based experiences and health of cancer survivors. *Complementary Therapies in Clinical Practice*, **20**(4), 188–192.

Reid, C. E., Clougherty, J. E., Shmool, J. L. C., & Kubzansky, L. D. (2017). Is all urban green space the same? A comparison of the health benefits of trees and grass in New York city. *International Journal of Environmental Research and Public Health*, **14**, 1411.

Reid, C. E., Kubzansky, L. D., Li, J., Shmool, J. L., & Clougherty, J. E. (2018). It's not easy assessing greenness: A comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York City. *Health and Place*, **54**, 92–101.

Rendón, O. R., Garbutt, A., Skov, M., … Beaumont, N. (2019). A framework linking ecosystem services and human well-being: Saltmarsh as a case study. *People and Nature*, **1**(4), 486–496.

Requia, W. J., Roig, H. L., Adams, M. D., Zanobetti, A., & Koutrakis, P. (2016). Mapping distance-decay of cardiorespiratory disease risk related to neighborhood environments. *Environmental Research*, **151**, 203–215.

Richardson, E. A., Pearce, J., Mitchell, R., & Kingham, S. (2013). Role of physical activity in the relationship between urban green space and health. *Public Health*, **127**(4), 318–324.

Richardson, M., & McEwan, K. (2018). 30 Days Wild and the Relationships Between Engagement With Nature'S Beauty, Nature Connectedness and Well-Being. *Frontiers in Psychology*, **9**, 1–9.

Richardson, M., McEwan, K., & Garip, G. (2018). 30 Days Wild: who benefits most? *Journal of Public Mental Health*, **17**(3), 95–104.

Rieskamp, J., Busemeyer, J. R., & Mellers, B. A. (2006). Extending the Bounds of Rationality: Evidence and Theories of Preferential Choice. *Journal of Economic Literature*, **44**(3), 631–661.

Roe, J., & Aspinall, P. (2011). The restorative benefits of walking in urban and rural settings in adults with good and poor mental health. *Health and Place*, **17**(1), 103–113.

Roe, J., Aspinall, P., & Ward Thompson, C. (2016). Understanding Relationships between Health, Ethnicity, Place and the Role of Urban Green Space in Deprived Urban Communities. *International Journal of Environmental Research and Public Health*, **13**(7), 681.

Roe, J. J., Ward Thompson, C., Aspinall, P. a., … Clow, A. (2013). Green space and stress: Evidence from cortisol measures in deprived urban communities. *International Journal of Environmental Research and Public Health*, **10**, 4086–4103.

RSPB. (2020). *Recovering together: A report of public opinion on the role and importance of nature during and in our recovery from the Coronavirus crisis in England.* Retrieved from https://www.rspb.org.uk/our-work/rspb-news/news/stories/poll-shows-people-in-england-support-nature-in-covid-recovery/

Rugel, E. J., Carpiano, R. M., Henderson, S. B., & Brauer, M. (2019). Exposure to natural space, sense of community belonging, and adverse mental health outcomes across an urban region. *Environmental Research*, **171**, 365–377.

Ryan, R. M., & Deci, E. L. (2001). On Happiness and Human Potentials: A Review of Research on Hedonic and Eudaimonic Well-Being. *Annual Review of Psychology*, **52**(1), 141–166.

Sandifer, P. a., Sutton-Grier, A. E., & Ward, B. P. (2015). Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: Opportunities to enhance health and biodiversity conservation. *Ecosystem Services*, **12**, 1–15.

Sandvik, E., Diener, E., & Seidlitz, L. (1993). Subjective Well-Being: The Convergence and Stability of Self-Report and Non-Self Report Measures. *Journal of Personality*, **61**(3), 317–342.

Sarkar, C., Webster, C., & Gallacher, J. (2018). Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. *The Lancet Planetary Health*, **2**(4), e162–e173.

Saw, L. E., Lim, F. K. S., & Carrasco, L. R. (2015). The relationship between natural park usage and happiness does not hold in a tropical city-state. *PLoS ONE*, **10**(7), 1–16.

Schebella, M. F., Weber, D., Schultz, L., & Weinstein, P. (2019). The wellbeing benefits associated with perceived and measured biodiversity in Australian urban green spaces. *Sustainability (Switzerland)*, **11**, 802.

Schipperijn, J., Bentsen, P., Troelsen, J., Toftager, M., & Stigsdotter, U. K. (2013). Associations between physical activity and characteristics of urban green space. *Urban Forestry and Urban Greening*, **12**(1), 109–116.

Schleicher, J., Schaafsma, M., Burgess, N. D., … Vira, B. (2018). Poorer without It? The Neglected Role of the Natural Environment in Poverty and Wellbeing. *Sustainable Development*, **26**(1), 83–98.

Schraufnagel, D. E., Balmes, J. R., Cowl, C. T., … Wuebbles, D. J. (2019). Air Pollution and Noncommunicable Diseases: A Review by the Forum of International Respiratory Societies' Environmental Committee, Part 1: The Damaging Effects of Air Pollution. *Chest*, **155**(2), 409–416.

Secretariat of the Convention on Biological Diversity. (2020). *Global Biodiversity Outlook 5*, Montreal.

Sen, A. (1977). Rational Fools : A Critique of the Behavioral Foundations of Economic Theory. *Philosophy & Public Affairs*, **6**(4), 317–344.

Seto, K. C., Fleishman, E., Fay, J. P., & Betrus, C. J. (2004). Linking spatial patterns of bird and butterfly species richness with Landsat TM derived NDVI. *International Journal of Remote Sensing*, **25**(20), 4309–4324.

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America*, **109**(40), 16083–16088.

Shah, A. S., Langrish, J. P., Nair, H., … Mills, N. L. (2013). Global association of air pollution and heart failure: a systematic review and meta-analysis. *The Lancet*, **382**(9897), 1039–1048.

Shah, a. S. V., Lee, K. K., McAllister, D. a., … Mills, N. L. (2015). Short term exposure to air pollution and stroke: systematic review and meta-analysis. *BMJ*, **350**, h1295–h1295.

Shanahan, D. F., Lin, B. B., Gaston, K. J., Bush, R., & Fuller, R. A. (2014). Socio-economic inequalities in access to nature on public and private lands: A case study from Brisbane, Australia. *Landscape and Urban Planning*, **130**(1), 14–23.

Sheridan, C., Roscoe, C., Gulliver, J., de Preux, L., & Fecht, D. (2019). Inequalities in Exposure to Nitrogen Dioxide in Parks and Playgrounds in Greater London. *International Journal* *of Environmental Health Research*, **16**, 3194.

Smith, C., Dawson, D., Archer, J., … Massini, P. (2011). *From green to grey; observed changes in garden vegetation structure in London, 1998-2008*. Retrieved from https://www.gigl.org.uk/partnershipcasestudy/garden-research/

Soga, M., & Gaston, K. J. (2016). Extinction of experience: The loss of human-nature interactions. *Frontiers in Ecology and the Environment*, **14**(2), 94–101.

Song, C., Joung, D., Ikei, H., … Miyazaki, Y. (2014). Physiological and psychological effects of walking on young males in urban parks in winter. *Journal of Physiological Anthropology*, **33**(1), 8.

Southon, G. E., Jorgensen, A., Dunnett, N., Hoyle, H., & Evans, K. L. (2018). Perceived species-richness in urban green spaces: Cues, accuracy and well-being impacts. *Landscape and Urban Planning*, **172**, 1–10.

Spangenberg, J. H., & Settele, J. (2010). Precisely incorrect? Monetising the value of ecosystem services. *Ecological Complexity*, **7**(3), 327–337.

Srinivasan, S., & Stewart, G. (2004). The quality of life in England and Wales. *Oxford Bulletin of Economics and Statistics*, **66**(1), 0305–9049.

StataCorp. (2011). Stata Statistical Software: Release 12. College Station, TX: StataCorp LP.

StataCorp. (2019). Stata Statistical Software: Release 16. College Station, TX: StataCorp LLC.

State of Nature Partnership. (2019). *State of Nature: a summary for England*. Retrieved from https://nbn.org.uk/stateofnature2019/

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics*, **20**(4), 518–529.

Strumpf, E. C., Harper, S., & Kaufman, J. S. (2017). Fixed effects and difference in differences. In *Methods in Social Epidemology*, pp. 341–368.

Sturmberg, J. P. (2014). Emergent properties define the subjective nature of health and disease. *Journal of Public Health Policy*, **35**(3), 414–419.

Su, J. G., Dadvand, P., Nieuwenhuijsen, M. J., Bartoll, X., & Jerrett, M. (2019). Associations of green space metrics with health and behavior outcomes at different buffer sizes and remote sensing sensor resolutions. *Environment International*, **126**, 162–170.

Takayama, N., Korpela, K., Lee, J., … Kagawa, T. (2014). Emotional, restorative and vitalizing effects of forest and urban environments at four sites in Japan. *International Journal of Environmental Research and Public Health*, **11**(7), 7207–7230.

Tallis, M., Taylor, G., Sinnett, D., & Freer-Smith, P. (2011). Estimating the removal of atmospheric particulate pollution by the urban tree canopy of London, under current and future environments. *Landscape and Urban Planning*, **103**(2), 129–138.

Taylor, L., Hahs, A. K., & Hochuli, D. F. (2018). Wellbeing and urban living: nurtured by nature. *Urban Ecosystems*, **21**(1), 197–208.

Taylor, L., & Hochuli, D. F. (2017). Defining greenspace: Multiple uses across multiple disciplines. *Landscape and Urban Planning*, **158**, 25–38.

Taylor, M. S., Wheeler, B. W., White, M. P., Economou, T., & Osborne, N. J. (2015). Research note: Urban street tree density and antidepressant prescription rates—A cross-sectional study in London, UK. *Landscape and Urban Planning*, **136**, 174–179.

Theobald, E. J., Ettinger, A. K., Burgess, H. K., … Parrish, J. K. (2015). Global change and local solutions: Tapping the unrealized potential of citizen science for biodiversity research. *Biological Conservation*, **181**, 236–244.

Tilley, S., Neale, C., Patuano, A., & Cinderby, S. (2017). Older people's experiences of mobility and mood in an urban environment: A mixed methods approach using electroencephalography (EEG) and interviews. *International Journal of Environmental Research and Public Health*, **14**(2). doi:10.3390/ijerph14020151

Tillmann, S., Tobin, D., Avison, W., & Gilliland, J. (2018). Mental health benefits of interactions with nature in children and teenagers: A systematic review. *Journal of Epidemiology and Community Health*, 958–966.

Treasury, H. M. (2008). *Developments in the economics of well-being. Treasury Economic Working Paper No.4 (Lepper, J., & McAndrew, S.).*, London: HM Treasury.

Triguero-Mas, M., Dadvand, P., Cirach, M., … Nieuwenhuijsen, M. J. (2015). Natural outdoor environments and mental and physical health: Relationships and mechanisms. *Environment International*, **77**, 35–41.

Triguero-Mas, M., Donaire-Gonzalez, D., Seto, E., … Nieuwenhuijsen, M. J. (2017). Natural outdoor environments and mental health: Stress as a possible mechanism. *Environmental Research*, **159**, 629–638.

Troudet, J., Grandcolas, P., Blin, A., Vignes-Lebbe, R., & Legendre, F. (2017). Taxonomic bias in biodiversity data and societal preferences. *Scientific Reports*, **7**(1), 1–14.

Tryjanowski, P., Morelli, F., Mikula, P., … Jerzak, L. (2017). Bird diversity in urban green space: A large-scale analysis of differences between parks and cemeteries in Central Europe. *Urban Forestry and Urban Greening*, **27**, 264–271.

Tsai, W. L., Floyd, M. F., Leung, Y. F., McHale, M. R., & Reich, B. J. (2016). Urban Vegetative Cover Fragmentation in the U.S.: Associations with Physical Activity and BMI. *American Journal of Preventive Medicine*, **50**(4), 509–517.

Tsurumi, T., & Managi, S. (2015). Environmental value of green spaces in Japan: An application of the life satisfaction approach. *Ecological Economics*, **120**, 1–12.

Turrini, T., & Knop, E. (2015). A landscape ecology approach identifies important drivers of urban biodiversity. *Global Change Biology*, **21**(4), 1652–1667.

Twohig-Bennett, C., & Jones, A. (2018). The health benefits of the great outdoors: A systematic review and meta-analysis of greenspace exposure and health outcomes. *Environmental Research*, **166**, 628–637.

Tyrväinen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., & Kagawa, T. (2014). The influence of urban green environments on stress relief measures: A field experiment. *Journal of Environmental Psychology*, **38**, 1–9.

Tzivian, L., Winkler, A., Dlugaj, M., … Hoffmann, B. (2015). Effect of long-term outdoor air pollution and noise on cognitive and psychological functions in adults. *International Journal of Hygiene and Environmental Health*, **218**(1), 1–11.

Ulrich, R. S. (1984). View through a window may influence recovery from surgery. *Science (New York, N.Y.)*, **224**(4647), 420–421.

United Nations. Convention on Biological Diversity (1994).

United Nations. (2015). *Transforming Our World: The 2030 Agenda for Sustainable Development*, New York.

United Nations. (2017). *New Urban Agenda*. Retrieved from http://habitat3.org/wp-content/uploads/NUA-English.pdf

University of Essex. Institute for Social and Economic Research. (2018). Understanding Society: Waves 1-8, 2009-2017 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access, Census 2001 Lower Layer Super Output Areas. [data collection]. 10th Edition. UK Data Service. SN: 6670. Retrieved from http://doi.org/10.5255/UKDA-SN-6670-11

University of Essex. Institute for Social and Economic Research. NatCen Social Research. Kantar Public. (2016). Understanding Society: Waves 1-6, 2009-2015: Special Licence Access, Census 2001 Lower Layer Super Output Areas. [data collection]. 7th Edition. UK Data Service. SN: 6670. Retrieved from http://doi.org/10.5255/UKDA-SN-6670-7

University of Essex. Institute for Social and Economic Research. (2014). British Household Panel Survey, Waves 1-18, 1991-2009: Special Licence Access, Lower Layer Super Output Areas and Scottish Data Zones. [data collection]. 3rd Edition. UK Data Service. SN: 6136. Retrieved from http://doi.org/10.5255/UKDA-SN-6136-2

University of Essex. Institute for Social and Economic Research. (2019a). Understanding Society, Waves 1-9, 2009-2018, and Harmonised British Household Panel Survey, Waves 1-18, 1991-2009: Secure Access. [data collection]. 10th Edition. UK Data Service. SN:6676. Retrieved from http://doi.org/10.5255/UKDA-SN-6676-10

University of Essex. Institute for Social and Economic Research. (2019b). Understanding Society, Waves 1-9, 2009-2018, and Harmonised British Household Panel Survey, Waves 1-18, 1991-2009: Special Licence Access, Census 2001 Lower Layer Super Output Areas and Scottish Data Zones. [data collection]. 11th Edition. UK Data Service. Retrieved from http://doi.org/10.5255/UKDA-SN-6670-11

University of Essex. (2016). *Understanding Society: The UK Household Longitudinal Study. Waves 1-5. Quality Profile.*, Colchester.

van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010a). Green space as a buffer between stressful life events and health. *Social Science and Medicine*, **70**(8), 1203–1210.

van den Berg, A. E., van Winsum-Vestra, M., de Vries, S., & van Dillen, S. M. E. (2010b). Allotment gardening and health: a comparative survey among allotment gardeners and their neighbors without an allotment. *Environmental Health*, **9**(74), 1–12.

van den Berg, M., Wendel-Vos, W., van Poppel, M., Kemper, H., van Mechelen, W., & Maas, J. (2015). Health benefits of green spaces in the living environment: A systematic review of epidemiological studies. *Urban Forestry and Urban Greening*, **14**(4), 806–816.

van den Bosch, M., & Nieuwenhuijsen, M. (2017). No time to lose – Green the cities now. *Environment International*, **99**, 343–350.

van Praag, B. M. S., & Baarsma, B. E. (2005). Using Happiness Surveys To Value Intangibles : the Case of Airport Noise. *The Economic Journal*, **115**(2000), 224–246.

Villaseñor, N. R., & Escobar, M. A. H. (2019). Cemeteries and biodiversity conservation in cities: how do landscape and patch-level attributes influence bird diversity in urban park cemeteries? *Urban Ecosystems*, **22**(6), 1037–1046.

Völker, S., Heiler, A., Pollmann, T., Claßen, T., Hornberg, C., & Kistemann, T. (2018). Do perceived walking distance to and use of urban blue spaces affect self-reported physical and mental health? *Urban Forestry and Urban Greening*, **29**, 1–9.

Völker, S., & Kistemann, T. (2015). Developing the urban blue: Comparative health responses to blue and green urban open spaces in Germany. *Health and Place*, **35**, 196–205.

von Möllendorff, C., & Hirschfeld, J. (2016). Measuring impacts of extreme weather events using the life satisfaction approach. *Ecological Economics*, **121**, 108–116.

Wang, H., & Tassinary, L. G. (2019). Effects of greenspace morphology on mortality at the neighbourhood level: a cross-sectional ecological study. *The Lancet Planetary Health*, **3**(11), e460–e468.

Wang, P., Meng, Y. Y., Lam, V., & Ponce, N. (2019). Green space and serious psychological distress among adults and teens: A population-based study in California. *Health and Place*, **56**, 184–190.

Wang, R., Yang, B., Yao, Y., … Dong, G. (2020). Residential greenness, air pollution and psychological well-being among urban residents in Guangzhou, China. *Science of the Total Environment*, **711**, 1–12.

Ward Thompson, C., Roe, J., & Aspinall, P. (2013). Woodland improvements in deprived urban communities: What impact do they have on people's activities and quality of life?

Landscape and Urban Planning, **118**, 79–89.

Welsch, H. (2002). Preferences over prosperity and pollution: Environmental valuation based on happiness surveys. *Kyklos*, **55**(4), 473–494.

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological Economics*, **58**, 801–813.

Welsch, H. (2007). Environmental welfare analysis: A life satisfaction approach. *Ecological Economics*, **62**(3–4), 544–551.

Welsch, H., & Kühling, J. (2009). Using happiness data for environmental valuation: Issues and applications. *Journal of Economic Surveys*, **23**(2), 385–406.

Wheeler, B. W., Lovell, R., Higgins, S. L., … Depledge, M. H. (2015). Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *International Journal of Health Geographics*, **14**(1), 17.

Wheeler, B. W., White, M., Stahl-Timmins, W., & Depledge, M. H. (2012). Does living by the coast improve health and wellbeing. *Health and Place*, **18**(5), 1198–1201.

White, M. P., Alcock, I., Grellier, J., … Fleming, L. E. (2019). Spending at least 120 minutes a week in nature is associated with good health and wellbeing. *Scientific Reports*, **9**(1), 1–11.

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013a). Coastal proximity, health and well-being: Results from a longitudinal panel survey. *Health and Place*, **23**, 97–103.

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013b). Would You Be Happier Living in a Greener Urban Area? A Fixed-Effects Analysis of Panel Data. *Psychological Science*, **24**(6), 920–928.

White, M. P., Elliott, L. R., Wheeler, B. W., & Fleming, L. E. (2018). Neighbourhood greenspace is related to physical activity in England, but only for dog owners. *Landscape and Urban Planning*, **174**, 18–23.

White, M. P., Pahl, S., Ashbullby, K., Herbert, S., & Depledge, M. H. (2013c). Feelings of restoration from recent nature visits. *Journal of Environmental Psychology*, **35**, 40–51.

White, M. P., Pahl, S., Wheeler, B. W., Depledge, M. H., & Fleming, L. E. (2017). Natural environments and subjective wellbeing: Different types of exposure are associated with different aspects of wellbeing. *Health and Place*, **45**, 77–84.

White, M., Smith, A., Humphryes, K., Pahl, S., Snelling, D., & Depledge, M. (2010). Blue space: The importance of water for preference, affect, and restorativeness ratings of natural and built scenes. *Journal of Environmental Psychology*, **30**(4), 482–493.

WHO Regional Office for Europe. (2016). *Urban green spaces and health*, Copenhagen.

Williams, N. S. G., Hahs, A. K., & Vesk, P. A. (2015). Urbanisation, plant traits and the composition of urban floras. *Perspectives in Plant Ecology, Evolution and Systematics*, **17**(1), 78–86.

Wilson, E. O. (1984). *Biophilia*, Cambridge, MA: Harvard University Press.

Wood, E., Harsant, A., Dallimer, M., Cronin de Chavez, A., McEachan, R. R. C., & Hassall, C. (2018). Not All Green Space Is Created Equal: Biodiversity Predicts Psychological Restorative Benefits From Urban Green Space. *Frontiers in Psychology*, **9**, 1–13.

Wood, L., Hooper, P., Foster, S., & Bull, F. (2017). Public green spaces and positive mental health – investigating the relationship between access, quantity and types of parks and mental wellbeing. *Health and Place*, **48**, 63–71.

World Cities Culture Forum. (2017). The percentage of public green space. Retrieved from http://www.worldcitiescultureforum.com/data/of-public-green-space-parks-and-gardens

World Health Organisation. (2016). Urban health, global health observatory data. Retrieved from https://www.who.int/gho/urban_health/en/. [Last accessed: 9th September 2020].

World Health Organisation. (2018). WHO European Healthy Cities Network. Retrieved from http://www.euro.who.int/en/health-topics/environment-and-health/urban-health/who-european-healthy-cities-network. [Last accessed: 10th September 2020].

Wyles, K. J., White, M. P., Hattam, C., Pahl, S., King, H., & Austen, M. (2019). Are Some Natural Environments More Psychologically Beneficial Than Others? The Importance of Type and Quality on Connectedness to Nature and Psychological Restoration. *Environment and Behavior*, **51**(2), 111–143.

Yuan, L., Shin, K., & Managi, S. (2018). Subjective Well-being and Environmental Quality: The

Impact of Air Pollution and Green Coverage in China. *Ecological Economics*, **153**, 124–138.

Zhang, J. W., Howell, R. T., & Iyer, R. (2014). Engagement with natural beauty moderates the positive relation between connectedness with nature and psychological well-being. *Journal of Environmental Psychology*, **38**, 55–63.

Zhang, L., & Tan, P. Y. (2019). Associations between urban green spaces and health are dependent on the analytical scale and how urban green spaces are measured. *International Journal of Environmental Research and Public Health*, **16**, 578.

Zhang, X., Zhang, X., & Chen, X. (2017a). Valuing Air Quality Using Happiness Data: The Case of China. *Ecological Economics*, **137**, 29–36.

Zhang, Y., Van den Berg, A. E., Van Dijk, T., & Weitkamp, G. (2017b). Quality over quantity: Contribution of urban green space to neighborhood satisfaction. *International Journal of Environmental Research and Public Health*, **14**, 535.