From landscapes to cityscapes: Quantifying the connection between scenic beauty and human wellbeing

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Abstract

Intuitively, we often seek out beautiful scenery when we want a respite from our busy lives, but do such settings actually help to boost our wellbeing? While architects, urban planners and policymakers have puzzled over this question for centuries, quantitative analyses have been held back by a lack of data on the beauty of our environment. However, the vast volumes of geotagged images readily shared on the Internet, alongside developments in computer vision and deep learning, are opening up opportunities to quantify aspects of the visual environment that were previously hard to measure. In the research reported here, we ask: might the beauty of outdoor environments have a quantifiable association with increased wellbeing?

This thesis explores the following related strands of work: (1) How accurately can we automatically predict the beauty of scenes for which we do not have survey or crowdsourced scenicness data? (2) Is there a quantifiable connection between the beauty of the environment, as measured by scenicness, and people's wellbeing? (3) Can we develop a broader understanding of what beautiful outdoor spaces are composed of?

In the first strand, we investigate whether a deep learning model can be trained to automatically infer the scenicness of images. We find that a retrained convolutional neural network performs remarkably well, and that this network highlights not only natural but also built-up locations as being scenic. In the second strand, we explore the connection between beautiful scenery and different types of wellbeing: happiness, mental distress and life satisfaction. We find that individuals experience more happiness when visiting more scenic locations, even when we account for a range of factors such as weather conditions and the income of local inhabitants. However, in terms of mental distress and life satisfaction, we do not find evidence that individuals who live in more scenic locations report higher levels of wellbeing. In the third and final strand, we analyse crowdsourced data and discover that beautiful places are composed of natural features such as 'Coast', 'Mountain' and 'Canal Natural' as well as man-made structures such as 'Tower', 'Castle' and 'Viaduct'. Importantly, while scenes containing 'Trees' tend to rate highly, places containing more bland natural green features such as 'Grass' and 'Athletic Fields' are considered less scenic.

The research reported in this thesis takes an important step towards providing evidence that the beauty of the environment, and therefore decisions made about

the design of environments, might have a crucial impact on people's everyday wellbeing. Our results also demonstrate that online data combined with neural networks can provide a deeper understanding of which environments humans might find beautiful.

“A thing of beauty is a joy for ever” – John Keats

Chapter 1
Introduction

1.1 Thesis overview

For centuries, humans have expressed their appreciation for beauty. From Plato to Ruskin, philosophers have long theorised about the importance of aesthetics (Eco, 2004). Governments around the world value beautiful places, as evidenced by the protection of areas of outstanding natural beauty and the aesthetically-driven regeneration of deprived urban areas. Architects and designers often place emphasis on the aesthetics of what they create, not just the utilitarian function (Carmona, 2010). As individuals, we often seek out beautiful places when we want to lift our spirits, or simply to relax.

However, until now, quantitative evidence supporting the argument that beautiful places are beneficial to human beings has been lacking. Thus, beauty is often considered to be a luxury that might be tackled only if resources allow (Harvey & Julian, 2015). Yet, what if beauty is actually an essential component of our lives?

In 2010, the Commission for Architecture and the Built Environment (CABE), tasked with advising the UK government on architecture, urban design and public spaces, commissioned a thought-provoking study using the concept of "beauty" as a channel to engage people in a discussion about their local environment. The research was undertaken in Sheffield, a city undergoing extensive regeneration. Some notable excerpts from the study are as follows:

> *Jack found it very difficult to experience beauty on the Park Hill estate where he lives. The threat of violence on Park Hill was a constant concern for him. That, in addition to the area visually appearing ugly to him made it difficult for him to experience beauty at home. In Park Hill, Jack described waking up and feeling like going back to bed so he doesn't have to look at or think about his surroundings*. (Ipsos MORI, 2010, p.39)

> *When you're surrounded by beautiful buildings, or something that looks extraordinary, straight away you're more up about things. It's a lovely thing that – just being able to pass by somewhere and feel better. It's like seeing a nice tree or something beautiful in nature, it has the same effect. And that's got to be*

important for the general public – seeing something you like and feeling happier. (Ipsos MORI, 2010, p.42)

While the definition of “beauty” varied from individual to individual, there was nonetheless strong agreement that the beauty of the environment had a profound effect on the respondents’ everyday lives, including their wellbeing. In fact, eighty per cent of those interviewed regarded beauty as a right, not just a luxury.

What if there is economic value in creating and preserving beautiful places? If beautiful places are essential to our quality of life, can we still afford to think of beauty as just an afterthought? This PhD thesis attempts to build quantitative evidence to help answer the question: are beautiful environments associated with increased wellbeing?

Why has evidence for the link between beautiful places and our wellbeing been lacking in the scientific literature thus far? Existing large-scale research that has looked into the influence of the environment on our wellbeing has been limited to aspects of the environment that have traditionally been feasible to measure, for example the percentage of green land cover using aerial footage; tree density and different types of land cover via satellite imagery; or population density via the census (e.g. White et al., 2013a; Kardan et al., 2015; Alcock et al., 2015). Measuring the beauty of an entire country through traditional survey methods would be a highly time-consuming and costly enterprise and thus, to date, most such research has been limited to small-scale local surveys or laboratory experiments using photographs of the environment (e.g. Bond et al., 2012a; Pretty et al., 2005) (See Chapter 2, Section 2.3 for a full review of the previous literature).

In recent years, data generated through our increasing interactions on the Internet has begun to allow us to quantify aspects of the visual environment in which we live that were previously difficult to measure, yet may affect crucial aspects of our lives such as our wellbeing (Seresinhe, Preis & Moat, 2015). The vast quantity of geotagged images uploaded to the Internet provides a basis for gathering novel and comprehensive data on how humans perceive and interpret their natural and built environment (Antoniou, Morley & Haklay, 2010; De Nadai et al., 2016; Dunkel, 2015; Quercia, O’Hare & Cramer, 2014; Seresinhe, Preis & Moat, 2015; Wood et al., 2013). Recent advances in computer vision methods, particularly in deep learning, have begun to allow us to extract information from images at a far greater speed than ever before (LeCun, Bengio & Hinton, 2015).

For the research reported in this thesis, we exploit crowdsourced data from the online game *Scenic-Or-Not*, where respondents rate geotagged photographs taken across the United Kingdom on the basis of how scenic they find them to be. Through this game, over 1.5 million ratings for photos of more than 200,000 1 km grid squares of Great Britain have been collected, producing national-scale measurements of environmental aesthetics of a kind not previously available to researchers. This new data source gives us the novel opportunity to not only evaluate the connection between scenicness and wellbeing, but also an extensive dataset with which to use deep learning to understand what beautiful places are composed of.

Specifically, this research investigates the following questions: (1) How accurately can we algorithmically predict the beauty of scenes for which we do not have survey or crowdsourced scenicness data? (2) Is there a quantifiable connection between the beauty of the environment and people's wellbeing? (3) Can we develop a broader understanding of what beautiful outdoor spaces are composed of?

1.2 Thesis roadmap

In Chapter 2, we review the existing literature related to investigating the connection between the environment and our wellbeing. We first review the different ways in which wellbeing is measured, in order to understand which aspects of wellbeing we might want to consider when exploring the connection between wellbeing and beautiful places. We also review existing literature to explore findings to date on how different aspects of the environment, from green space and blue space to natural versus urban environments, might contribute to increased wellbeing. As our methodology draws on various sources of data gathered online, we also explore existing research on how online data has been used to understand human behaviour. Finally, we present our previous study exploring the connection between beautiful places and reported health.

While *Scenic-Or-Not* provides us with an initial map of scenic areas around Great Britain, studies that explore the benefits of scenicness might require scenicness measurements at a higher resolution, particularly in cities where the scenic beauty can vary extensively within each square kilometre. Thus, in Chapter 3 and 4, we explore different methods for estimating the scenicness of places for which we do not have existing data. In Chapter 3, we exploit crowdsourced data from the image sharing platform *Flickr* to investigate whether models including crowdsourced data can generate more accurate estimates of scenicness than models that consider only basic demographic measurements such as population density or whether an area is urban or rural. In Chapter 4, we exploit recent advances in computer vision, specifically deep learning, to build an algorithm to predict scenicness at high resolution across the country.

The connection between beautiful environments and our wellbeing might vary depending on what aspect of wellbeing we measure, such as our experienced everyday happiness or an evaluation of how satisfied we are with our lives. Therefore, in Chapter 5 and 6 we investigate the connection between scenic environments and different types of wellbeing: (1) our experienced wellbeing as measured though happiness ratings submitted via the mobile phone app *Mappiness* (Mackerron & Mourato, 2013), and (2) our evaluative wellbeing, specifically life satisfaction and mental distress, as measured through annual survey responses to The UK Household Longitudinal Study, Understanding Society (University of Essex, 2017).

Finally, we wish to understand how beautiful places might differ from merely natural environments. When we envisage beautiful environments, we often envisage stunning scenery abundant in nature. However, are beautiful environments simply natural environments? Or, can we uncover a broader definition of scenic beauty that might account for built-up elements as well? In Chapter 7, we again exploit deep learning methods to quantify what beautiful outdoor places are composed of. In Chapter 8, we explore how the definition of scenic beauty might differ in Rio de Janeiro, a setting remarkably different from Great Britain.

Chapter 9 concludes this thesis with an overview of our main findings. We also note possible limitations of our research, discuss suggestions for future research, and discuss wider policy implications of our findings.

1.3 Policy relevance

This research could have significant implications for planning and development policy, including whether the aesthetics of the environment warrants investment. While current public policy does suggest that policymakers see some value in promoting beauty in wider infrastructure – as we see in the protection of natural and historical locations and the regeneration of deprived urban areas – these decisions are not based on robust evidence, and therefore risk the misallocation of public resources (Bakhshi, 2010). Furthermore, public policy often avoids addressing beauty that can be created locally in our everyday lives (Harvey & Julian, 2015). For example, while government departments readily promote the preservation and creation of green spaces (UK Parliamentary Office of Science and Technology, 2016), there is often very little guidance regarding their quality, and thus more deprived areas might be prone to have low-quality green spaces that have little appeal to local residents (Roberts-Hughes, 2013). Finally, in public policy, policymakers might be reluctant to engage with the concept of beauty explicitly, as beauty has long been considered an intangible measure that is difficult to quantify due to its subjective nature.

In light of the above, we believe this research can inform public policy in the following ways: 1) Does beauty warrant investment? If we were to find a quantitative connection between beautiful places and wellbeing, then this could motivate governments to consider aesthetics in relevant public policies, such as the introduction of aesthetically pleasing green spaces. 2) Can we find a tangible definition of beauty by identifying features that we might find collectively beautiful, such as trees or certain aspects of built-up structures? It would make it easier for policymakers to address concepts of beauty in planning and development guidelines if such guidelines could be supported by clearer direction as to what makes something beautiful. 3) Can we successfully measure the beauty of the environment on a large scale? If so, we can help ease the process policymakers undergo in identifying areas that might be lacking in beauty and in need of infrastructure investment, due to the fact that this process can be implemented at large scale and at relatively low cost.

Thus, this research will help policymakers make evidence-based assessments about what makes environments beautiful, thereby informing investment decisions and potentially helping to address countrywide inequalities in beauty. Empirical evidence on the connection between beautiful environments and human wellbeing is vital for informing policy choices in this area.

1.4 Research contributions

This thesis contributes to scientific research with the following technical and conceptual advances:

1) A deep learning method to automatically infer the scenicness of images, such that this algorithm can be applied to new images for which crowdsourced scenic ratings have not been obtained. The ability to predict scenicness at a high resolution and for new areas has the potential to enable future social science research to investigate the connection between the beauty of the environment and various measures that might be important to us – from economic prosperity to physical health.

2) The first large-scale evidence demonstrating that the beauty of the environment, and not just whether it is natural or green, is quantitatively associated with people's everyday wellbeing. Crucially, the relationship we find holds not only in natural environments, but in built-up areas too, even after controlling for a range of factors such as the activity the individual was engaged in at the time, weather conditions, whether it was the weekend, and the income of local inhabitants. We argue that a focus on green space alone is misplaced and has come about due to previous lack of availability of large-scale data on the aesthetic quality of the environments we inhabit.
3) A broader understanding of what beautiful outdoor places are composed of, based on the analysis of hundreds of features extracted from over 200,000 images. Crucially, we demonstrate that the old adage 'natural is beautiful' seems to be incomplete: flat and uninteresting green spaces are not necessarily beautiful, while characterful buildings and stunning architectural features can improve the beauty of a scene.

Chapter 2
A review of existing research

2.1 Introduction

In this chapter, we examine existing literature to determine what is already known about the connection between the environment and our wellbeing, and we also consider issues in measuring both the environment and wellbeing that should be taken into account in further research on this topic, such as the work presented in this thesis.

There is unlikely to be one measure that can accurately capture wellbeing, as it is a multi-faceted notion composed of various elements, such as everyday happiness and life satisfaction. Therefore, we first explore the different ways in which wellbeing can be measured, in order to understand which aspects of wellbeing we might want to consider in this research.

We also want to develop a better understanding of what aspects of the environment are connected with our wellbeing, and how these aspects might relate to beautiful environments. For example, there is ample research exploring the connection between natural places and our wellbeing. We want to understand not only if such research has been able to show if such a connection exists, but also if there might be gaps in the research where beautiful places might offer an insightful explanation.

We also review previous studies that have attempted to explore the connection between beautiful places and our wellbeing, and consider the obstacles that previous researchers have faced in this endeavour. For example, such studies have had to rely heavily on local survey data, or data gained from people's responses to images of environments in laboratory settings, in order to understand people's preferences for different environments. However, crowdsourced data from the Internet is a valuable resource for gathering large-scale data on beautiful places. We therefore also explore to what extent crowdsourced data can provide useful insights into our preferences. We present an initial study we conducted prior to this thesis, where we explore the connection between beautiful places and reported health using a crowdsourced database of the beauty of Great Britain.

Finally, as the broader goal of this research is to provide useful guidelines for urban planners and policymakers on how they might design spaces that best benefit human wellbeing, we explore to what extent we can quantify beautiful places. While individual ideas of beauty might indeed be subjective to some extent, as they are shaped by our cultural, social and life experiences (Zube & Pitt, 1981; Zube, Pitt & Evans, 1983), we explore how previous research has attempted to understand our collective understanding of beauty.

2.2 On measuring subjective wellbeing

Interest in maximising human wellbeing has a long history, initially sparked by the utilitarian philosopher Jeremy Bentham, who advocated that we should strive for “the greatest happiness of the greatest number” (Bentham, 2005). For centuries however, the importance of wellbeing as a measure to evaluate the health of nations has largely been sidestepped in favour of economic measures of performance such as Gross Domestic Product (GDP). Interest in measuring wellbeing was only recently reignited, first in 2000 by the Organisation for Economic Co-operation and Development (OECD) who included in its mission the aim ‘to promote policies that will improve the economic *and social* wellbeing of people around the world’. This eventually led to the 'better life' initiative, a project that measures wellbeing across OECD countries (Allin & Hand, 2017). Later, the Stiglitz Commission report of 2009 as cited by Dolan & Metcalf (2012) stated:

> 'Research has shown that it is possible to collect meaningful and reliable data on subjective as well as objective wellbeing. Subjective wellbeing encompasses different aspects (cognitive evaluations of one’s life, happiness, satisfaction, positive emotions such as joy and pride, and negative emotions such as pain and worry): each of them should be measured separately to derive a more comprehensive appreciation of people’s lives.'

The Commission’s report not only claimed that subjective wellbeing is measureable, but also that it provides vital information for deciding the direction of social progress and public policy. Thus, measuring wellbeing has steadily grown in importance for policymakers, with governments initiating programmes to measure wellbeing. Notably, in 2010, the UK Prime Minister (Cameron, 2010) gave a speech on the importance of measuring wellbeing in Britain and emphasised the need to evaluate Britain's progress not only by how the economy is performing but also in terms of quality of life.

While the importance of measuring wellbeing is clear to many, what is less clear is which measure accurately captures wellbeing. Research that aims to understand how we can improve our happiness and quality of life therefore often involves measuring several aspects of wellbeing. These include not only objective and subjective measures, but also various elements of our subjective experience, including our emotions, experiences and judgements.

The various aspects of our subjective wellbeing are thought to belong to the following three broad categories: (1) *evaluative wellbeing* – cognitive judgements on how someone might feel about something, e.g. “how satisfied are you with your life?”; (2) *experienced wellbeing* – the experience of emotions in an individual’s everyday life, e.g. “how happy are you right now?”; and (3) *eudaimonic wellbeing* – the sense of meaning or purpose in life, e.g. “to what extent do you feel the things you do in your life are worthwhile?”. The association of wellbeing with certain aspects of our lives might differ based on what type of wellbeing we are considering (Kahneman & Riis, 2005; O'Donnell et al., 2014; White et al., 2017). For example, in a study by Kahneman and Deaton (2010), the researchers found that positive affect (as measured by the amount of happiness, smiling and laughter) increased with income levels but only up to a certain point (~$75,000), whereas life evaluation can continue to increase steadily with increased income. White et al. (2013b) found that individuals report less mental distress when living nearer to the coast, but they did not find a similar association with life satisfaction.

Time frames might also matter when measuring wellbeing. For example, the question “how happy are you right now?“ might elicit a completely different response to “how happy were you in the past two weeks?” or “how happy are you with life in general?”. Advocates of measuring experienced wellbeing argue that moment-by-moment records provide a less distorted picture of an individual's experiences (Hektner, Schmidt & Csikszentmihalyi, 2007; Kahneman et al., 2004), as unlike post-hoc questioning, such moment-by-moment records do not rely on people's recollections of their experiences, which are susceptible to biases (Redelmeier & Kahneman, 1996). Such biases include the peak/end rule and duration neglect: the finding that when people judge an experience as being pleasant or unpleasant, they appear to neglect the duration of the experience, but rather judge it based on how it felt at its peak and towards its end (Kahneman & Thaler, 2006). Others argue that studies based on evaluative questions where participants reflect on their wellbeing might reveal more stable preferences and provide more insight into how people actually make life decisions (Akay, Bargain & Jara, 2017; O’Donnell et al., 2014; Helliwell & Leigh, 2010). As there is disagreement in previous research about which measurements of wellbeing most accurately capture people's experiences, it might be useful to first understand how beautiful places might be connected with measurements of different aspects of wellbeing, such as experienced wellbeing and evaluative wellbeing. We can then evaluate, based on which connections we discover, how we might want to interpret the usefulness of our results. For example, if we discover a connection between experienced wellbeing and beautiful places only, we might want to consider policy interventions that specifically target people's everyday wellbeing, such as visits to beautiful parks. However, if we discover a connection between evaluative wellbeing and beautiful places, we can then consider policy interventions such as designing a housing estate to be a more beautiful place for people to live in.

2.3 On the connection between environment and wellbeing

When understanding the connection between the environment and human wellbeing, researchers have often focused on aspects of our environments that have traditionally been feasible to measure at large scale, such as areas abundant in greenery (green space), large bodies of water (blue space) and natural versus urban habitats. Research regarding our exposure to greenery commonly involves measuring vegetated areas via satellite or aerial imagery, as in the Generalised Land Use Database (Department for Communities and Local Government, 2007) or counting the number of individual trees in an area. In terms of mental wellbeing, a higher proportion of green space is linked with reduced levels of stress (Thompson et al., 2012; van den Berg et al., 2010), less perceived depression (Triguero-Mas et al., 2015; de Vires et al., 2016) or anxiety (Triguero-Mas et al., 2015), less mental distress (as measured by the General Health Questionnaire, a screening device for identifying minor psychiatric disorders) (White et al., 2013a; Triguero-Mas et al., 2015), and higher life satisfaction in urban areas (White et al., 2013a). Frequent visits to green spaces are associated with an increased feeling that activities in life are worthwhile (White et al., 2017). There is also evidence of a connection between green space and aspects of physical wellbeing such as self-reported health (de Vries et al., 2003; Kardan et al., 2015; Mitchell, Astell-Burt & Richardson, 2011; Mitchell & Popham, 2007; Maas et al., 2006; Triguero-Mas et al, 2015), more physical activity (Richardson et al., 2013; Ellaway, Macintyre & Bonnefoy, 2005), less likelihood of being overweight and obese (Ellaway, Macintyre & Bonnefoy, 2005), all-cause mortality (Mitchell, Astell-Burt & Richardson, 2011), and reduced risk of cardiovascular diseases (Richardson et al., 2013). However, a study by Houlden, Weich and Jarvis (2017) found no evidence supporting an association between the amount of green space and multi-dimensional wellbeing (as measured by the Short Warwick Edinburgh Mental Well Being Scale, a tool focusing entirely on positive aspects of mental health). Furthermore, in the study by Mitchell and

Popham (2007), the authors found that greater amounts of green space correlate with higher rates of ill health in low-income suburban neighbourhoods. Mitchell and Popham (2007) suggested that the quality of the green space might matter as well as simply the quantity. The two studies (Houlden, Weich & Jarvis, 2017; Mitchell & Popham, 2007) indicate that the connection between green space and our wellbeing might be more complex, and other aspects such as the aesthetic quality of green spaces might also be important to consider.

Researchers have also quantitatively explored the association between wellbeing and blue spaces – environments where water is the central feature, such as a coast or river – and the results are mixed. There is some evidence supporting the link between coastal and salt-water areas and physical wellbeing, as measured by self-reported health (Wheeler et al., 2012, 2015; White et al., 2013b). However, although Triguero-Mas et al. (2015) found significant positive associations between green space and several measures of wellbeing, they did not find evidence of an association between blue space and mental distress, perceived depression or anxiety, or self reported health. On the other hand, De Vires et al. (2016) did find a significant association between blue space and less perceived depression or anxiety. White et al. (2013b) did find a connection between coastal areas and reduced mental distress, but they did not find an association between coastal areas and life satisfaction. Beautiful coastlines and scenic lakes are a popular draw for visitors and they clearly have some beneficial effects for people's mental wellbeing, but the lack of evidence for a connection between blue space and wellbeing in both White et al. (2013b) and Triguero-Mas et al. (2015) is intriguing. Could this discrepancy point to the importance of the aesthetic quality of those blue spaces? Perhaps certain types of blue spaces have the ability to improve our wellbeing while others do not.

Researchers have also investigated the role the environment plays in our wellbeing by exploring the differences in wellbeing in natural versus urban environments, as commonly measured through land cover data complied via satellite imagery such as CORINE. Natural environments have been associated with reduced anxiety and negative thoughts (Bratman et al., 2015a; Bratman et al., 2015b) and increased happiness (Mackerron & Mourato, 2013). Natural settings may have a restorative effect, thus helping us feel less mentally fatigued after spending time exposed to them (Hartig, Mang & Evans, 1991; Hartig et al., 1997; Herzog et al., 2003; Kaplan & Kaplan, 1989). Researchers have also discussed the link between affect and the environment (Hull & Harvey, 1989; Kaplan, 1987; Sheets & Manzer, 1991; Ulrich, 1983; White et al., 2010) – the environment's aesthetic role to move people emotionally may be central to explaining its restorative power. For example, Ulrich et al. (1991) found that when people were exposed to a stressful experience – a stressful movie in the case of this study – individuals who then viewed natural rather than urban scenes were able to recover faster from stress. The authors' hypothesis is that the subjects' emotional reactions to the natural settings aided recovery from stress.

However, such studies have not attempted to explore the role that the beauty of natural environments might have in increasing wellbeing. Intuitively it seems that a beautiful coastal view has greater ability to increase our wellbeing than a desolate field. Studies that have been restricted to using straightforward geographic datasets, such as distances to parks or coastal areas, tree density, and land cover categories, can only provide part of the picture of how the environment has an influence on our wellbeing. Thus, a missing component still remains: a better understanding of how the aesthetic quality of these environmental factors might influence our wellbeing.

2.4 Initial investigations of the connection between scenic beauty and wellbeing

In the past, research into understanding the relationship between beautiful scenes and our wellbeing has been limited to using proxy data on beautiful environments, for example comparing responses to nature vs. urban window scenes, such as views of deciduous trees versus a brown brick wall (Ulrich, 1984), looking at beautiful images in a laboratory setting, or local surveys on the beauty of the environment.

Studies of people viewing nature from windows, compared to viewing typical urban settings, have suggested that natural window views are associated with faster recovery from surgery (Ulrich, 1984), reduced stress and increased mental restoration (Ulrich et al., 1991), better attentional capacities in undergraduate dormitory residents (Tennesen & Cimprich, 1995), increased residential wellbeing and satisfaction (Kaplan, 2001), as well as increased employee wellbeing (Gilchrist, Brown & Montarzino, 2015). While many natural views might also be considered to be beautiful, these studies do not directly investigate the role beauty itself might play in our wellbeing.

Initial, albeit small scale, evidence on the connection between beautiful environments and our wellbeing comes from laboratory experiments and local surveys. Participants exposed to photographs of beautiful natural scenery while exercising on a treadmill (Pretty et al., 2005) reported increased levels of mood, comfort, excitement, tranquillity and safety, as well as less boredom (Galindo & Rodriquez, 2000). Participants tend to report higher affect (increased feelings of happiness) when exposed to images that they also find aesthetically pleasing (White et al., 2010). However, It could also be argued that emotional reactions to environmental scenes in everyday life may differ from person to person.

Analyses using survey data suggest that attractive settings are associated with increased mental wellbeing (Bond et al., 2012a) and might encourage us to engage in more physical activity (Ball et al., 2001). While these studies are promising in that they explore beauty found in scenes in everyday life, in the Ball et al. (2001) study, when claiming to measure the aesthetic nature of the local environment, they combine perceptions of attractiveness (measured by feedback scores for the statement “Your local area is attractive”) with perceptions about non-visual elements of the environment (measured by scores for the statements “Your neighbourhood is friendly” and “You find it pleasant walking near your home”). Thus it is not clear which statements are driving the connection between their measure of environmental aesthetics and physical activity. Furthermore, the Bond et al. (2012a) study only covers 15 deprived areas of Glasgow and so may not provide a comprehensive view of how beautiful environments impact our wellbeing.

However, in all these studies, other than the study reported by Pretty et al. (2005), the photographs or neighbourhoods used in these studies were rated for attractiveness by the same person reporting their mood, such that aesthetic and emotional responses may be difficult to disentangle.

Thus, these studies have not been able to explain confounding results sometimes found in large-scale studies exploring the connection between environment and wellbeing, such as the Mitchell and Popham (2007) study that found the surprising result that greater green space is correlated with higher rates of ill-health in low-income suburban neighbourhoods. If we were able to measure the quality of our environment on a large scale, this would help develop a broader understanding of how the beauty of environments, not just the availability of nature, has an impact on our wellbeing.

2.5 Using online data to understand human behaviour

The ubiquitous presence of the Internet in today’s society has led to the creation of a new source of information on human behaviour: large datasets generated from online activity. Data generated through our increasing online interactions with platforms such as *Google* (Choi & Varian, 2012; Curme et al., 2014; Ginsberg et al., 2009; Kristoufek, Moat & Preis, 2016; Letchford, Preis & Moat, 2016; Moat et al., 2014, 2016; Noguchi et al., 2014; Preis et al., 2012; Preis, Moat & Stanley, 2013; Preis & Moat, 2014, 2015)*, Wikipedia* (Moat et al., 2013)*, Facebook* (Bakshy, Messing & Adamic, 2015; Bond et al., 2012b)*, Flickr* (Alanyali, Preis & Moat, 2016; Barchiesi et al., 2015a, 2015b; Preis et al., 2013; Wood et al., 2013; Zhou et al., 2014), *Twitter* (Bollen, Mao & Zeng, 2011; Botta, Moat & Preis, 2015), and online news providers (Alanyali, Moat & Preis, 2013; Curme et al., 2017) have led to a range of new insights into human behaviour in the real world (King, 2011; Lazer et al., 2009; Moat et al., 2014; Watts, 2007).

Of particular interest are the studies by Wood et al. (2013) and Zhou et al. (2014). The study by Wood et al. (2013) leverages social media activity to track demand for recreational sites around the world. The authors specifically predict the number of visits to 836 recreational sites around the world using geotagged images uploaded to *Flickr*, the online photograph-sharing platform. They uncover relationships between measurements of the number of visits to a given attraction and the number of photographs taken at each site, and find that data on the originating country of each photographer may also relate to data on the origin of visitors. Similarly, Zhou et al. (2014) exploited geotagged images uploaded to *Flickr* and, through image analysis, extracted city attributes such as "green space", "transportation" and "architecture" to characterise the identity of a city.

In our own study "Quantifying the link between art and property prices in urban neighbourhoods" (Seresinhe, Preis & Moat, 2016), we explored how online data can be used to quantify aspects of the visual environment that have previously been difficult to measure, in this case the presence of art in a city over time. *The Economist* (2000) article "The Geography of Cool" discusses how artists have been changing the economic landscape of London – from James Whistler and Oscar Wilde in Chelsea to the 1990s "Britart" movement in Hoxton. While the popular media and policymakers commonly believe that art plays a central role in the transformation of deprived urban neighbourhoods, quantitative evidence for this has generally remained lacking.

In Seresinhe, Preis & Moat (2016), we used metadata of geotagged photographs uploaded to the popular image-sharing platform *Flickr* to quantify the association between art and the relative gain in residential property prices for each Inner London neighbourhood. We estimated the presence of art in neighbourhoods by determining the proportion of *Flickr* photographs with the word 'art' attached. We found that neighbourhoods that have a higher proportion of mentions of “art” associated with *Flickr* photographs also have greater relative gains in house prices. Our findings demonstrate how online data can indeed be used to quantify aspects of the visual environment in which we live that were previously difficult to measure.

Online games have also been shown to be a valuable resource for crowdsourcing perceptions of a city in high volume (Naik et al., 2014; Salesses, Schechtner & Hidalgo, 2013; Quercia, 2013). For example, in the online game Place Pulse 1.0 (Salesses, Schechtner & Hidalgo, 2013), respondents are asked to select between pairs of images for questions such as “Which place looks safer?” or “Which place looks more upper-class?”. This game has crowsdourced over 200,000 votes for 4,136 images for New York, Boston, Linz and Salzburg.

2.6 The first large-scale study exploring the connection between beautiful places and our wellbeing

Using crowdsourced ratings of the beauty of the environment, we conducted the first large-scale study to explore the connection between beautiful places and people's reported health. In our study “Quantifying the Impact of Scenic Environments on Health” (Seresinhe, Preis & Moat, 2015) we asked: might the aesthetics of our environment have a measurable impact upon our health?

We drew on data from *Scenic-Or-Not* (http://scenic.mysociety.org), a website that crowdsources ratings of “scenicness” for geotagged photographs. *Scenic-Or-Not* presents users with random geographically-tagged and mainly eye-level photographs of Great Britain, which visitors can rate on an integer scale of 1 – 10 (10 indicating “very scenic” and 1 indicating “not scenic”). The entire dataset contains 217,000 images, sourced from Geograph (http://www.geograph.org.uk), covering nearly 95% of the 1 km grid squares of Great Britain.

We combined this with citizen-reported health data from the Census for England and Wales 2011 (Office for National Statistics, 2012). In order to control for socioeconomic characteristics that may be linked with reported health, we used deprivation data from the 2010 English Indices of Deprivation (Department for Communities and Local Government, 2011) in order to take account of the fact that health may be associated with the following characteristics: income, employment, housing, education, crime and living conditions. We also explored whether there is any variation in the association between reported health and scenicness across urban, suburban and rural areas.

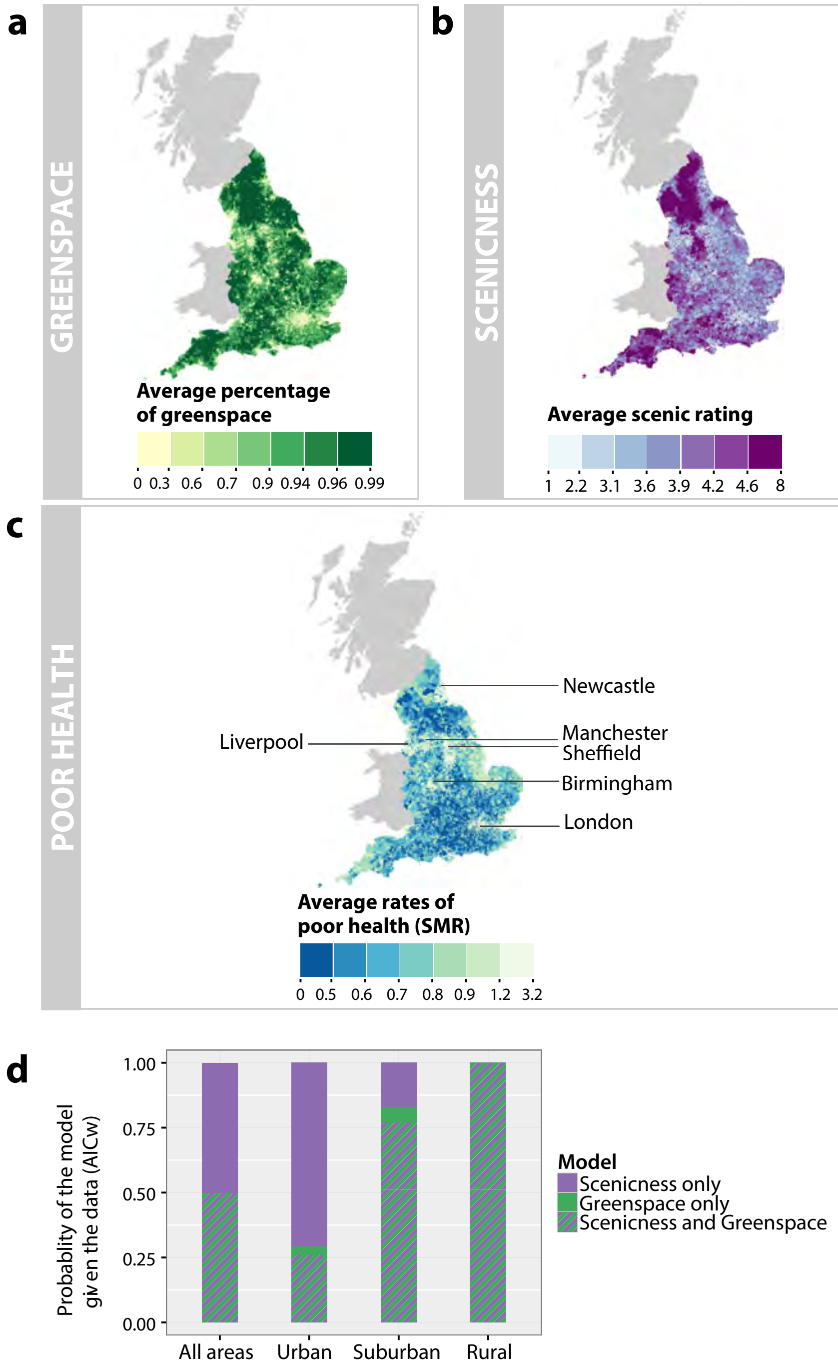


Figure 2.1 Scenicness, green space and health in England.
(a) We depict green space, using *Generalised Land Use Database 2005* green land cover data, at the level of English Lower Layer Super Output Areas (LSOAs) with quantile breaks. (b) We calculate the average scenic rating of all *Scenic-or-Not* photographs taken in each LSOA and depict these ratings using quantile breaks. (c) Respondents to the *2011 Census for England and Wales* classified their health as “Very good or good”, “Fair” or “Bad or very bad”. We calculated health rates using the Standardized Morbidity Ratio (SMR), which is the ratio of the observed to the expected number of cases of bad health for a particular population, taking the age and gender of inhabitants into account. We depict the SMR for each LSOA using quantile breaks. (d) To determine which model provides the best fit for predicting poor health, we calculate Akaike weights (AICw), which can be used to interpret the probability of each model given the data. Contains National Statistics, NISRA, NRS and Ordnance Survey data © Crown copyright and database right 2013.

Across the entire English dataset, we found that inhabitants of more scenic environments report better health (β = -0.008, N = 16,907, p < 0.001), even when taking a wide range of deprivation variables into account. This relationship holds across all urban categories (Urban: β = -0.007, N = 3,944, p = 0.012; Suburban: β = -0.005, N = 7,781, p = 0.007; Rural: β = -0.012, N = 5,182, p < 0.001).

As several studies have indicated that an abundance of green space results in increased human wellbeing (de Vries et al., 2003; Ellaway, Macintyre & Bonnefoy, 2005; Maas et al., 2006; Mitchell & Popham, 2007; Mitchell & Popham, 2008; van den Berg et al., 2010; Sugiyama et al., 2008; White et al., 2013a), we also evaluated to what degree scenicness relates to objective measurements of green land cover obtained from aerial imagery. The relationship between scenicness (Fig. 2.1a) and green land cover (Fig. 2.1b) is apparent upon inspection of the two maps, and indeed scenicness and green land cover are significantly correlated (β = 0.2, N = 128,213, p < 0.001, Kendall's rank correlation). However, the correlation is not very strong in terms of effect size, suggesting that scenicness and green land cover are not necessarily the same. For example, in the East of England, green land cover and scenicness diverge considerably.

We therefore investigated to what extent geographic differences in health (Fig. 2.1c) can be explained by scenicness and green space. In all cases, we found that there is more evidence for models that include scenicness than for the model with only green space (Fig. 2.1d). Our results provide initial evidence in line with the striking hypothesis that the aesthetics of the environment has a quantifiable connection to human wellbeing.

2.7 What might beautiful environments be composed of?

We have linked scenic beauty to reports of better health (Seresinhe, Preis & Moat, 2015). We have also shown that geographic differences in health can be better explained by models that include measurements of scenicness than by models that use measurements of green space only. But what are these beautiful spaces actually composed of and how might this differ from green space?

People typically equate beautiful places with natural places. The presence of nature has been far easier to measure and often thought to be the one universal feature that we can collectively agree on as being beautiful, usually explained with reference to the *'biophilia hypothesis'* which suggests that evolutionary pressures have led to a human preference for a connection with nature (Kellert & Wilson, 1995). Our love of tree-rich landscapes might be driven by the fact that trees have long provided our antecedents with respite against the sun and rain, or protection from predators (Joye, 2007; Orians & Heerwagen, 1992). However, there is reason to believe that natural elements have not purely been a positive force in our lives (Ulrich, 1993).

There might be other general aspects of the environment that have driven our evolutionary preferences. Appleton's prospect and refuge theory (Appleton, 1975) argues that humans have involved to prefer environments where one can easily survey “prospects” or seek “refuge” to avoid possible dangers. This concept has been partially supported by empirical evidence demonstrating our preference for scenes with prospects, while the evidence supporting our preference for scenes with refuge is still unclear (Dosen & Ostwald, 2016).

We also seem to prefer scenes that have a moderate degree of complexity, as they might hold our interest for longer (Ulrich, 1983; Kaplan, Kaplan & Wendt, 1972; Kaplan & Kaplan, 1989; Nasar, 1994). However, the relationship between complexity and aesthetic preference is thought to follow an inverted U-shaped curve (Berlyne, 1971), where scenes with too much information might overwhelm the visual system, making them difficult to process, and thus aesthetically displeasing (Reber, Schwarz & Winkelman, 2004). There is also some evidence that we prefer scenes with order (Kaplan & Kaplan, 1989), repeated visual patterns (Alexander, 1977) and symmetrical forms (Enquist & Arak, 1994). The theories above underline the idea that beautiful environments may not be entirely synonymous with natural environments, and if we want to understand how to build environments that benefit our wellbeing, we might require a more in-depth understanding of what makes an environment beautiful.

2.8 Discussion

A review of previous literature related to the topics covered by this thesis has revealed that in order to understand the connection between scenic beauty and our wellbeing, we will need to consider different aspects of our wellbeing. These aspects include our experienced wellbeing, such as everyday happiness, and our evaluative wellbeing, such as life satisfaction. Prior research exploring the connection between the environment and our wellbeing has made a sizeable contribution to our knowledge. However, as a majority of these studies have been restricted to using datasets where geographic features can be easily measured (such as amounts of green space or distances to coastal areas), or have been mainly laboratory-based small-scale studies, we still lack a large-scale understanding of how the beauty of the environment might be connected to our wellbeing.

As we can now measure the beauty of environments using data readily available on the Internet, we now have the opportunity to investigate the connection between beautiful environments and our wellbeing at an unprecedented scale. Finally, we have also discovered that the definition of beautiful environments might be more complex than the common explanation that only natural environments provide beauty. Thus, if we are to find a connection between beauty and our wellbeing, we might also be in a position to provide useful insights to urban planners and policymakers tasked with designing places that enhance people's lives.

SECTION I
Can we predict the scenicness of new places?

To date, measuring scenic beauty on a large scale, such as an entire country, has been a difficult endeavour. Typically, such data has been gathered through traditional survey methods, which are costly and time-consuming. The following two sections explore different methods for estimating the scenicness of places for which we do not have existing scenic ratings. These include the exploitation of crowdsourced data from the image-sharing platform *Flickr*, as well as new computer vision techniques such as deep learning.

Chapter 3
Predicting scenic ratings using crowdsourced data from *Flickr*

3.1 Introduction

Does living in picturesque areas improve people's wellbeing? Philosophers, psychologists, urban planners and policymakers have deliberated over this question for years, but have been hindered by the lack of data on the beauty of our environment. For many years, it has been possible to obtain large-scale datasets of objective measures of the environment, such as distances to parks or coastal areas, proportion of green land cover, and population density. However, time-consuming and costly large-scale surveys have been the only method of eliciting information about people's perceptions of their environment. While more automated methods of eliciting beauty of the environment using data from Geographic Information Systems (GIS) are promising (Bishop and Hulse, 1994; Grêt-Regamey et al., 2007; Palmer, 2004; Schirpke et al., 2013), to date, these analyses have been carried out only on a small scale, possibly due to a reliance on survey data to validate their findings.

However, the ubiquitous presence of the Internet in today's society has led to new source of data on our preferences and perceptions: the vast quantity of crowdsourced data openly shared on the Internet. Increasingly, this online activity is being geographically tagged, which has already lead to a range of fascinating insights into our interactions with our surrounding environment (Batty, 2013; Botta et al., 2015; Casalegno et al., 2013; Dunkel, 2015; Dykes et al., 2008; Girardin et al., 2008; Gliozzo et al., 2016; Goodchild, 2007; Graham & Shelton, 2013; Haklay et al., 2008; King, 2011; Lazer et al., 2009; Moat et al., 2014; O'Brien et al., 2014; Preis et al., 2013; Seresinhe, Preis & Moat, 2015, 2016; Stadler et al., 2011; Sui et al., 2013; Tenerelli et al., 2016; Vespignani, 2009; Wood et al., 2013; Zaltz Austwick et al., 2013).

In our past research exploring the connection between beautiful places and people's reported health (Seresinhe et al., 2015), we used data from such a source: crowdsourced data from *Scenic-Or-Not,* a website that collects ratings of scenicness for 1 km grid squares of Great Britain. The volume of *Scenic-Or-Not* ratings is considerable: to date, over 1.5 million ratings have been collected for over

200,000 locations in the UK. However, if it were possible to measure scenicness on a global scale, what might this reveal about wellbeing around the world?

Photographs uploaded to image sharing websites such as *Flickr* cover a much greater area at greater density than our *Scenic-Or-Not* dataset. In this chapter, we begin to investigate whether data from *Flickr* could be used to estimate scenicness ratings for any location, without the requirement of gathering new *Scenic-Or-Not* ratings. Geotagged *Flickr* images have already been shown to be of value in identifying people's preferences for specific places (Girardin et al., 2008; Gliozzo et al., 2016; Tenerelli et al., 2016; Wood et al., 2013). We envisage that we might be able to capture the scenicness of an area through *Flickr* data, as people might share more photos of places they find to be picturesque, or may reveal the scenicness of an area through descriptions they add to images.

We also explore data from *OpenStreetMap*, an editable *Wiki* world map created by thousands of volunteers (Haklay, 2010; Neis et al., 2012), from people with local knowledge to GIS professionals. We ask whether images uploaded to *Flickr*, combined with crowdsourced geographic data from *OpenStreetMap*, can help us determine which geographic areas people consider to be scenic.

We build a base model to estimate how scenic an area is using measures of population density, number of residents, and urban, suburban or rural categories. We then explore to what extent crowdsourced data from *Flickr* and *OpenStreetMap* can help improve our base model. We identify which crowdsourced variables can add power to our model using a statistical learning method. Finally, we investigate whether models including crowdsourced variables can generate more accurate estimates of scenicness than our base model comprising measurements of population and area category alone. The research reported in this chapter was published in Seresinhe, Moat and Preis (2017).

3.2 Data and methods

Census and environment data

In our base model, we investigate whether data on population density, number of residents, and urban, suburban or rural categories can be used to estimate scenicness.

Data on population density and number of residents has been extracted from the *2011 Census for England and Wales* (Office for National Statistics, 2012) and *Scotland's Census 2011* (National Records of Scotland, 2012). We conduct our analyses on the level of Lower Layer Super Output Areas (LSOAs), which are defined by the Office for National Statistics for statistical analyses. LSOAs are geographic areas ranging from 0.018 to 684 square km, containing between 983 and 8,300 residents (1,500 on average).

We use data on urban and rural classifications of LSOAs (Office for National Statistics, 2013; Scottish Government, 2012) to explore the role urban, suburban or rural classification might play in the scenicness of an area. For the purposes of this study, "urban" LSOAs in England and Wales are defined using the category "Urban Major Conurbation" (Office for National Statistics, 2013). The remaining urban categories are deemed suburban. "urban" LSOAs in Scotland are defined using the category "Large Urban Areas" and "suburban" LSOAs are defined using the categories "Other Urban Areas", "Accessible Small Towns" and "Remote Small Towns" (Scottish Government, 2012).

Flickr and OpenStreetMap data

In our extended models, we include measures derived from all publicly available *Flickr* photographs uploaded in 2013 that were geotagged as being located in Great Britain. Data on *Flickr* images was retrieved from *Flickr's* Application Programming Interface (https://www.flickr.com/services/api/flickr.photos.search.html) throughout 2014. In order to ensure that the photographs were taken outdoors, we exclude images that were taken in buildings using crowdsourced data from *OpenStreetMap*. *OpenStreetMap* data on Buildings, Points of Interests and Natural Points of Interest was retrieved from GeoFabrik (http://www.geofabrik.de), where data was last updated on 20 July 2016.

From the 3,549,000 *Flickr* images we have available for our analysis, we identify 427,727 images located inside buildings and exclude them from our analysis. However, it is possible that the data from *OpenStreetMap* does not always correctly identify building locations. For example, Zielstra et al. (2013) and Haklay (2010) observe that the *OpenStreetMap* road network data might not always be complete. We therefore test a random sample of 10,000 images to gain further insight into whether they are taken in outdoor locations using the *Places Convolutional Neural Network* (CNN) (Zhou et al., 2014). The *Places CNN* has been trained on around 2.5 million images to detect 205 scene categories. The labels of the top five predicted place categories can be used to check if a given image was taken indoors or outdoors, with more than 95% accuracy (Zhou et al., 2014). Using this method, we find that 23% of images classified as being outdoors using the *OpenStreetMap* building data are classified as indoor images using *Places CNN*. When we evaluate image classifications in urban, suburban and rural areas separately, we find more mismatches between the *OpenStreetMap* and *Places CNN* classifications in urban and suburban areas than in rural areas. In urban areas, 35% of images classified as outdoor using *OpenStreetMap* data are classified as indoor using *Places CNN.* In suburban areas, the corresponding figure is 24%, in comparison to 14% in rural areas. We discuss the potential implications of this classification mismatch in the *Discussion* section.

Scenic-Or-Not data

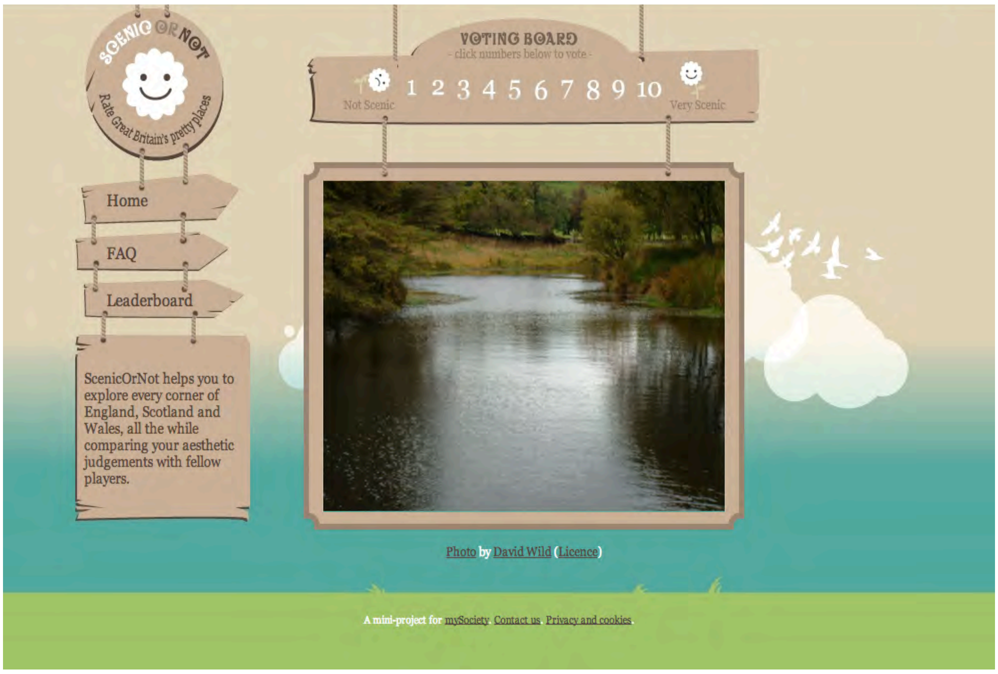


Figure 3.1. The *Scenic-Or-Not* voting screen.
Scenic-Or-Not presents users with random geotagged photographs of Great Britain, which visitors rate on an integer scale 1 – 10, where 10 indicates "very scenic" and 1 indicates "not scenic". Each image, sourced from *Geograph* (http://www.geograph.org.uk), represents a 1 km grid square of Great Britain. The *Scenic-Or-Not* database has over 217,000 images covering 92.5% of the 234,429 land mass 1 km grid squares of Great Britain.

We use data from *Scenic-Or-Not* to determine how accurately our model using *Flickr* and *OpenStreetMap* data is able to predict scenic areas. *Scenic-Or-Not* presents users with random geotagged photographs of Great Britain, which visitors can rate on an integer scale 1 – 10, where 10 indicates "very scenic" and 1 indicates "not scenic" (Fig. 3.1). Each image, sourced from *Geograph* (http://www.geograph.org.uk), represents a 1 km grid square of Great Britain. The *Scenic-Or-Not* database has over 217,000 images covering 92.5% of the 234,429 land mass 1 km grid squares of Great Britain. We retrieved data on scenicness ratings by accessing the *Scenic-Or-Not* website (http://scenic.mysociety.org) on 2

August 2014, obtaining over 1.5 million ratings. We only include images in our analysis that have been rated more than three times. For this analysis, we aggregate these ratings on the level of LSOA.

Identifying scenic images

When uploading images to *Flickr,* photographers commonly choose to include additional textual data such as a title, description and tags (e.g. 'scenic', 'sky', 'city') to describe the image. We attempt to determine which images could be considered scenic by evaluating this textual data associated with each *Flickr* photograph. We deem a photograph to be scenic if there is a mention of "scenic" or a similar word in this textual metadata.

To determine which words we should consider as similar to "scenic", we build a *word2vec* model. A *word2vec* model is constructed by processing a large corpus of text in order to build a representation of the semantic meaning of each word on the basis of the contexts in which it appears. Here, we process the full *Wikipedia* corpus, using the latest data as of 14 July 2016 (retrieved from https://dumps.wikimedia.org/enwiki/latest/). Having constructed this model, we are able to query it in order to identify words that have a similar meaning to any word of interest, such as "scenic". We classify a word as being similar if the similarity between the words is more than 0.5, according to the constructed *word2vec* model. We first search for words similar to "scenic", for which three words are returned: "picturesque", "scenery" and "hiking". We then search again for these three words to identify further similar words, whereby the model returns words such as "birdwatching", "landscape" and "unspoilt". Table 3.1 lists all the words identified by this approach.

In order to identify images that the textual information suggests might be scenic, we search the title, description and tags of each image using a regular expression for the word "scenic" (e.g. \bscenic\b) and, separately, for the word "scenic" or words similar to "scenic" (e.g. \b(scenic|picturesque|birdwatching|landscape)\b). The expression "\b" allows us to search for whole words only. In this process, we count only a single occurrence of "scenic" (or a word similar to "scenic") even if it has "scenic" (or a word similar to "scenic") mentioned several times in the metadata. We then have two different measures for each image: (1) whether the textual data mentions "scenic", or (2) whether the textual data mentions "scenic" or a word similar to "scenic".

Table 3.1. Identifying words similar to "scenic".
To determine which words we should consider as being similar to "scenic", we build a word2vec model. The table below lists all words we identify with this approach.

Words identified as similar to "scenic"	
backdrops	quaint
backpacking	riverway
birdwatching	rustic
breathtaking	sceneries
bucolic	scenery
bushwalking	snowmobiling
gorge	snowshoeing
greenery	surroundings
hikers	tourist
hiking	trails
hillwalking	tranquil
idyllic	trekking
landscape	unspoiled
landscapes	unspoilt
parks	vistas
picnicking	wilderness
picturesque	

Estimating scenic areas

We build a base model to help us determine how scenic an area is, using the measures of population density, number of residents, and urban, suburban or rural categories.

When working with spatial data, it is reasonable to assume that observations in neighbouring areas may be more or less alike simply due to their proximity, and hence exhibit autocorrelation (Bivand et al., 2013; Harris et al., 2005). We confirm this by first running a Moran's I test, which measures whether spatial autocorrelation is present in the data. Due to this autocorrelation, we cannot run a simple linear regression analysis, as spatial dependencies would exist in the error term. Hence, we run our analysis using a conditional autoregressive model (CAR), as detailed below.

We then explore to what extent crowdsourced data from *Flickr* and *OpenStreetMap* can help improve our base model. We identify which crowdsourced variables can add power to our model using a statistical learning method, as explained below.

Finally, we investigate whether models including crowdsourced variables can generate more accurate estimates of scenicness than our base model comprising measurements of population and area category alone, by comparing the Akaike weights of each model.

Conditional Auto Regressive (CAR) model

Initially proposed by Besag and colleagues (Besag, 1974; Besag et al., 1991), the CAR model captures spatial dependence between neighbours through an adjacency matrix of the areal units.

The CAR model quantifies the spatial relationship in the data by including a conditional distribution in the error term e_i. The conditional distribution of e_i is thus represented as:

$$e_i|e_{j\sim i} \sim N(\sum_{j\sim i} \frac{c_{ij}e_j}{\sum_{j\sim i} c_{ij}}, \frac{\sigma_{e_i}^2}{\sum_{j\sim i} c_{ij}})$$

where e_{-i} is the vector of all the errors terms except for itself; $e_{j\sim i}$ is the e_{-i} vector including only neighbouring areas of i; and c_{ij} are dependence parameters used to represent the spatial dependence between the areas.

Using statistical learning to identity candidate variables

We use the statistical learning method of cross-validation (Hastie et al., 2009; James et al., 2013) to identify candidate variables to use in our scenic estimation models using crowdsourced data. We randomly partition the observations in our data set into a 60/40 split where 60% of the data is used as the training set and 40% of the data is used as the validation set. We ensure that each partitioned dataset has an equal split of urban, suburban, and rural areas. We fit new models on the training dataset including all the variables in our base model (population density, number of residents, and urban, suburban or rural categories) plus every combination of all the crowdsourced variables we have identified, as listed in Table 3.2. We then fit these models to estimate responses for the observations on the validation set. We then compare the resulting validation test error rates, as measured by Root Mean Square Errors (RMSE). We choose two candidate models for estimating scenicness by choosing those with the lowest RMSEs.

Table 3.2. Crowdsourced variables considered in our analysis.

Variable	Method used to calculate measures
photos	Number of *Flickr* Photographs taken per LSOA
photographers	Number of *Flickr* Photographers per LSOA
photos.pop	Number of *Flickr* Photographs divided by Population Density per LSOA
photographers.pop	Number of *Flickr* Photographers divided by Population Density per LSOA
photos.hec	Number of *Flickr* Photographs divided by area of LSOA measured in hectares
photographers.hec	Number of *Flickr* Photographers divided by area of LSOA measured in hectares
photographers.POI	Number of *Flickr* Photographers divided by number of POIs per LSOA
photographers.natural	Number of *Flickr* Photographers divided by number of natural POIs per LSOA
photos.POI	Number of *Flickr* Photographs divided by number of POIs per LSOA
photos.natural	Number of *Flickr* Photographs divided by number of natural POIs per LSOA
photos.travel	Number of *Flickr* Photographs taken by travel photographers per LSOA
photographers.travel	Number of *Flickr* Travel Photographers per LSOA
photos.scenic	Number of images with the word "scenic" per LSOA
photos.scenic.similiar	Number of images with the word "scenic" or similar word to "scenic" per LSOA
photos.scenic.prop	Number of *Flickr* images with the word "scenic" divided by number of *Flickr* images uploaded per LSOA
photos.scenic.similiar.prop	Number of images with the word "scenic" or similar word to "scenic" divided by number of *Flickr* images per LSOA

Akaike weights (AICw)

In order to determine which model best estimates scenicness, we first calculate the AIC (Akaike Information Criterion) values for each model. AIC values help us to determine the likelihood of each model for a given set of data. The best model is the one that has the lowest AIC value. To help interpretation, we also calculate the Akaike weights (AICws), following the method proposed by Wagenmakers and Farrell (2004), as the AIC values themselves are difficult to interpret on their own. We derive AICws by first identifying the model with the lowest AIC. For each model, we then calculate an AIC difference, by determining the difference between the lowest AIC and the model's AIC. We next determine the relative likelihood of each model, following the method described in Wagenmakers and Farrell (2004). To determine the AICws, we normalise these likelihoods, such that across all models they sum to one. The resulting AICws can be interpreted as the probability of each model given the data.

3.3 Results

A comparison of the quantity of *Flickr* photographs taken (Fig. 3.2a) with a map of scenic ratings of images from *Scenic-Or-Not* (Fig. 3.2b) indicates that areas with a high density of photos – which tend to be highly-populated areas such as London and Manchester – are rated as being the least scenic. On the other hand, highly scenic areas, such as Scotland, have a low density of *Flickr* photographs taken. This indicates that population density may be a significant factor for estimating the scenicness of an area.

This also leads us to suppose that whether an area is urban, suburban or rural may also play a part in scenic ratings. Furthermore, Scotland, which is rated as highly scenic, is known for its beautiful rural settings. We therefore explore to what extent urban, suburban and rural areas affect scenic ratings.

We build our first model to help us determine how scenic an area is. We explore to what extent geographical differences in scenicness can be explained by the following objective measurements: population density, number of residents, and urban, suburban or rural categories.

As noted in the Methods section, spatial data may exhibit autocorrelation, where nearby observations may have similar values due to their proximity, and thereby violate the assumption made in linear regression that observations are independent. To test whether autocorrelation exists, we first build a linear regression model. A Moran's I test on the residuals of the linear regression model confirms that the model reveals significant spatial autocorrelation in the residuals of the linear regression models (*Moran's I* = 0.127, N = 15,188, $p < 0.001$). We therefore build a Conditional Auto Regressive (CAR) model (as described in the Methods section) that takes spatial autocorrelation into account (Bivand et al., 2013; Harris et al., 2005).

We find that low population density is associated with areas of high scenicness (β = -0.285, N = 15,188, $p < 0.001$) and that the lower the number of residents in an LSOA, the greater the scenicness (β = -0.0001, N = 15,188, $p < 0.001$). We also find that urban and suburban areas are associated with less scenicness (Urban β = -0.260, N = 15,188, $p < 0.001$; Suburban β = -0.083, N = 15,188, $p < 0.001$).

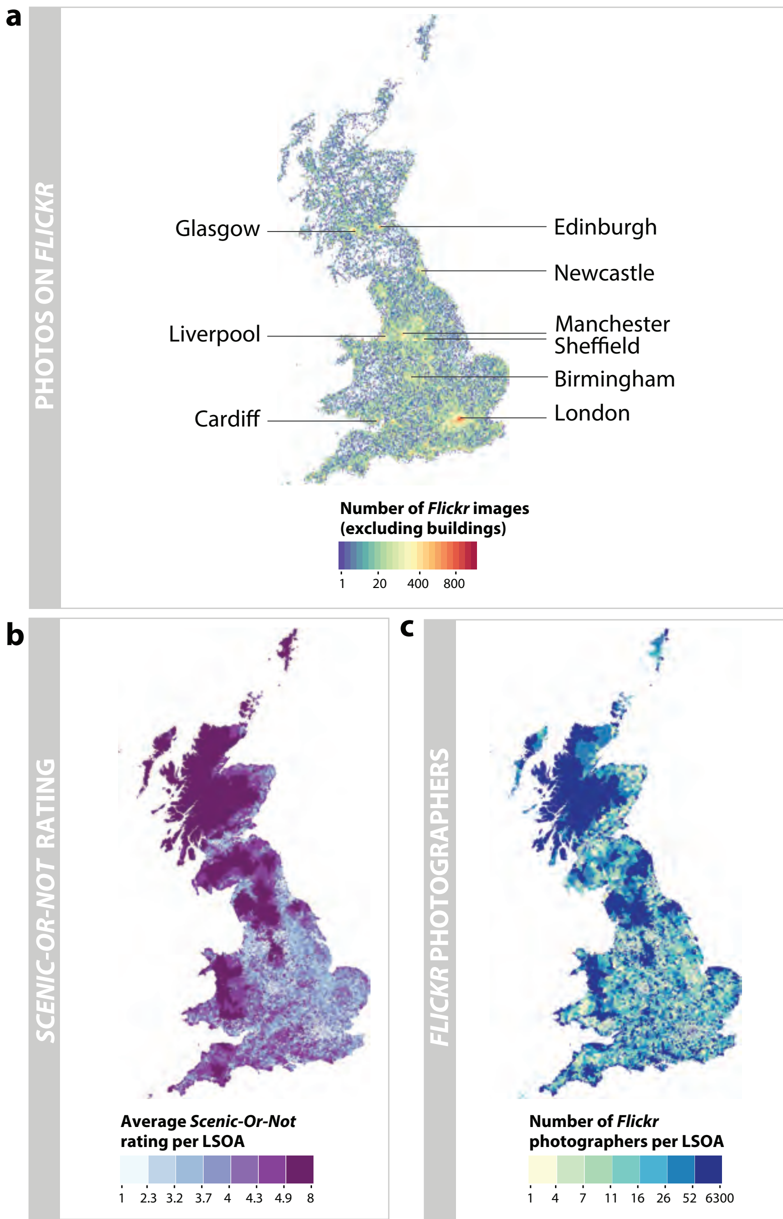


Figure 3.2 The relationship between *Flickr* photographs and ratings of scenicness from *Scenic-Or-Not* in Great Britain.
(a) We create a density plot of all *Flickr* photographs uploaded in 2013 geotagged as being taken in Great Britain. Inspection of the map indicates that most images are taken in areas of high population density such as London and Manchester. **(b)** The *Scenic-Or-Not* dataset comprises 217,000 images, sourced from *Geograph*, covering nearly 95% of the 1 km grid squares of Great Britain. We calculate the average scenic rating of all *Scenic-or-Not* photographs at the level of English Lower Layer Super Output Area (LSOA) and depict these ratings using quantile breaks. Examination of the two maps indicates that while the major cities have a higher density of photos, they are also rated as the least scenic. On the other hand, Scotland is rated as highly scenic while the density of photos remains low. This suggests that population density needs to be taken into account in the analysis. (**c**) An individual photographer may take several photographs of an area. While this may reveal individual preferences, we are primarily interested in the collective perception of scenicness. We therefore calculate the mean number of *Flickr* photographers for each LSOA and depict these ratings using quantile breaks. Visual inspection of these maps reveals that measures of the number of *Flickr* photographers per LSOA correspond well with scenic ratings from *Scenic-Or-Not*.

We now explore to what extent crowdsourced data from *Flickr* and *OpenStreetMap* can add additional explanatory power to our base model. First, we investigate whether the quantity of geotagged images uploaded to *Flickr* may be used as a proxy for visual preference of an area. As we are interested in the perception of outdoor environments rather than indoor environments, we also use crowdsourced data from *OpenStreetMap* to determine where buildings are located, and use this data to exclude *Flickr* images that have been taken inside buildings.

We note factors that may affect the quantity of *Flickr* images besides the scenicness of an area, and take a number of steps to correct for these issues in our analysis. First of all, we account for the fact that one photographer may take several photographs of an area. While this may reveal individual preference for an area, this may not reveal collective preference for an area. We therefore consider only the quantity of *Flickr* photographers for each LSOA, as we are primarily interested in the collective perception of scenicness.

Next, we consider the various reasons for people taking outdoor photographs. For example, people typically upload photographs to *Flickr* when they want to share a memory of an event or an activity (Purves et al., 2011) such as a birthday party, or they might share many pictures of themselves (commonly known as "selfies"). People might also add valuable information related to a photograph if they are motivated to share the image with the wider public (Nov et al., 2008). We therefore attempt to mitigate these potential biases in the uploaded *Flickr* photographs, as well as identify a stronger signal of scenic images by the following approaches: (1) we attempt to identify travel photographers and (2) we attempt to identify scenic images.

We hypothesise that *Flickr* photographs taken by photographers that travel are more likely to reveal scenic preferences. We therefore count the number of LSOAs in which each *Flickr* photographer has taken photos. We find the average number of LSOAs in which someone has taken a photograph is eight. We therefore deem a *Flickr* photographer a "travel photographer" if they have taken photographs in more than eight LSOAs.

We also attempt to identify which images are scenic, using textual data people have added to describe the image, as explained in more detail in the Methods section. We classify an image as scenic if there is a mention of "scenic" or a similar word to "scenic" in this textual metadata. We then count the number of images classified as scenic for each LSOA. We also include the count of images classified as scenic divided by all the images uploaded per LSOA, which gives us the proportion of images classified as scenic uploaded per LSOA.

Finally, we correct for a variety of characteristics that may affect the quantity of images uploaded in each LSOA: land area, quantity of points of interest and quantity of natural features. As LSOAs vary dramatically in size – between 1 hectare to 67,280 hectares in our analysis – and people may take more pictures in larger LSOAs, we consider to what extent land area affects the number of *Flickr* photographs taken. Certain points of interest (POIs), particularly tourist attractions, such as the London Eye, Big Ben and Edinburgh Castle attract large numbers of images (Antoniou, Morley & Haklay, 2010). This could distort the signal of whether or not the photographer considers the location scenic. We therefore consider how the quantity of POIs in each LSOA influence the number of *Flickr* photographs taken. *OpenStreetMap* also has data on how many natural POIs exist in each LSOA. As natural POIs may be associated with scenicness, we also consider how many *Flickr* images are taken considering how many natural POIs occur in each LSOA.

We can now test whether models that include crowdsourced variables perform better than a *base model* that only includes the objective measurements (population density, number of residents, and urban, suburban or rural categories). Table 3.2 lists all the crowdsourced variables that we test.

Using a statistical learning approach (as specified in the Methods section), we identify two candidate models that include crowdsourced data: (1) A simple *Flickr* model that, in addition to the base model, includes the number of *Flickr* photographers in each LSOA divided by the number of POIs in that LSOA (variable: *photographers.POI*); and (2) an extended *Flickr* model that, in addition to the simple *Flickr* model, includes the number of images classified as scenic per LSOA (variable: *photos.scenic.similiar).*

As in our previous analysis, we build these two candidate *Flickr* models as Conditional Auto Regressive (CAR) models. In the simple *Flickr* model, we find that a greater number of *Flickr* photographers, adjusted by POI, is significantly associated with higher ratings of scenicness (β = 0.095, N = 15,188, p < 0.001). In the extended *Flickr* model, we also find that a greater number of *Flickr* photographers, adjusted by POI, is significantly associated with higher ratings of scenicness (β = 0.092, N = 15,188, p < 0.001). We also find that the number of images with the word “scenic” or a word similar to “scenic” is significantly associated with higher ratings of scenicness (β = 0.001, N = 15,188, p < 0.001).

Finally, in order to determine whether models including crowdsourced variables can perform better than the models that only include objective measurements, we rank all three models – the base model, the simple *Flickr* model and the extended

Flickr model – in terms of their Akaike Information Criterion (AIC) value. This provides a measure of the relative model fit given a set of data. In order to compare the fit of the models to each other, AIC values are transformed to Akaike weights (AICw) following the method proposed by Wagenmakers and Farrell (2004). These weights can be interpreted as the probability of each model, given the data, as described in the Methods section. This model comparison indicates that models including crowdsourced geographic data from *Flickr* and *OpenStreetMap* provide more accurate estimates of the scenicness of an area than models that only include objective measurements such as population density and whether an area is urban, suburban or rural (Tab. 3.3).

Table 3.3. The performance of different models for estimating scenic ratings. Regression coefficients for CAR models estimating scenic ratings based on the validation data set. These results provide evidence that models including crowdsourced data have greater power to estimate scenic areas.

	Base model	**Simple *Flickr* model**	**Extended *Flickr* model**
Log of Population Density	-0.285 ***	-0.274 ***	-0.270 ***
All residents	0.000 ***	0.000 ***	0.000 ***
Suburban	-0.083 ***	-0.087 ***	-0.088 ***
Urban	-0.260 ***	-0.26 ***	-0.263 ***
photographers.POI		0.095 ***	0.092 ***
photos.scenic.similiar			0.001 ***
No of observations	15188	15188	15188
AIC	43045	42850	42830
AICd	215	20	0
AICw	< 0.001	< 0.001	> 0.999

Using the most probable model, the extended *Flickr* model, we further investigate how the ranked estimates of scenic areas compare to the ranked actual measures of scenic areas in different settings (Fig. 3.3). We find that our model is most successful at estimating scenic areas in rural settings (Urban: $\tau = 0.216$, $N = 1{,}060$, $p < 0.001$; Suburban: $\tau = 0.225$, $N = 2{,}567$, $p < 0.001$; Rural: $\tau = 0.363$, $N = 2{,}449$, $p < 0.001$, Kendall's rank correlation).

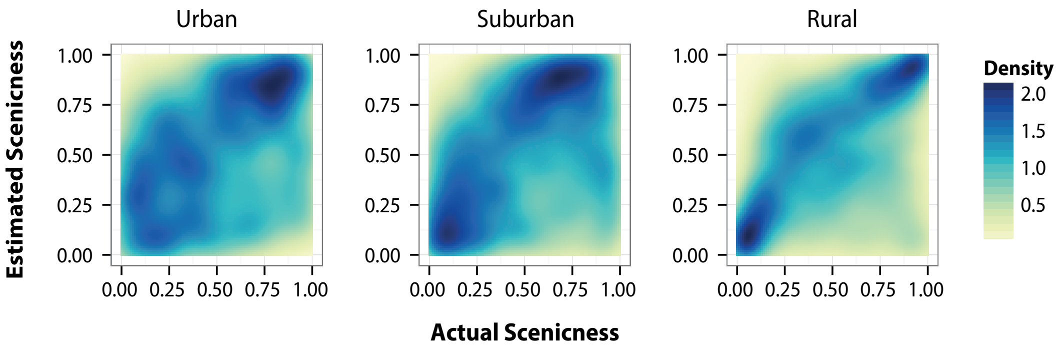


Figure 3.3. Ranked estimated scenic ratings versus ranked actual scenic ratings broken down by urban, suburban and rural areas.
Estimated scenic ratings are generated on a test dataset using the best *Flickr* model. Estimated and actual ratings are ranked and rescaled such that the lowest rank (most scenic area) is given the value 0, and the highest rank (least scenic area) is given the value 1. Rescaled ranks are then plotted using a 2D kernel density estimation.

3.4 Discussion

We investigate whether the vast quantity of data uploaded to the Internet could help us identify which areas of Great Britain people consider to be scenic. We analyse data from geotagged images uploaded to *Flickr*, combined with crowdsourced geographic data from *OpenStreetMap,* in order to see if such data can provide improvements of scenic estimations. We validate our findings using the website *Scenic-Or-Not*, which crowdsources ratings of scenicness in Great Britain.

Our findings suggest that crowdsourced data from sources such as *Flickr* and *OpenStreetMap* has the potential to reveal information about how people actually interact with their environment. Specifically, we find that models using crowdsourced data can generate more accurate estimates of scenicness than models comprising only basic census measurements such as population density or whether an area is urban or rural. Our results provide evidence that, indeed, measures of images uploaded to *Flickr* can provide information that can inform estimates of how scenic an area is.

However, while the improvement is significant, the effect size is not large. As our sample analysis of 10,000 *Flickr* images indicated that around 23% of our images we deemed to be outdoor images might in fact be indoor images, these might be adding uncertainty to our results.

Using a statistical learning approach, we identify the following crowdsourced variables as those that most improve estimates of scenicness: (1) the quantity of unique *Flickr* photographers, taking into account the number of POIs (as obtained through *OpenStreetMap* data) in each LSOA and (2) the number of images with the word “scenic” or a word similar to “scenic” per LSOA. We found no evidence in support of our hypothesis that travel photographers would give us a useful metric.

Visual analysis of the photographs uploaded by the most prolific *Flickr* travel photographers reveals that many of them use *Flickr* for curated content such as bus and train spotting (an observation also reported by Gliozzo et al., 2016). If the primary motivation of many of the photographers on *Flickr* is to only post content on a particular subject, then this would distort the estimate that *Flickr* data may provide on the scenicness of an area. We aim to mitigate this effect by only including images that we identify as being related to scenicness through our analysis of textual data associated with each image. While this approach improves our results, the overall impact from this approach still is not strong enough to dramatically improve our scenicness estimates.

Finally, we consider why models drawing on data from *Flickr* and *OpenStreetMap* produce more accurate estimates of scenicness in rural neighbourhoods than in urban and suburban areas. This may be due to the plurality of reasons for which people upload photographs in urban and suburban neighbourhoods: for instance, creating a memory of an event such as a birthday party or a sporting event. Urban and suburban LSOAs are also likely to have a greater number of unidentified indoor images in our analysis. While our analysis only uses images indicated by *OpenStreetMap* data to have been taken outside buildings, a neural network trained to extract information from images of outdoor and indoor environments, *Places CNN* (Zhou et al., 2014), produces different classifications for some of these images. Specifically, when analysing a sample of 10,000 images classified as outdoor using *OpenStreetMap* data, we find that *Places CNN* classifies 35% of these images taken in urban areas and 24% of these images taken in suburban areas as indoor images. In rural areas, only 14% of the images classified as outdoor images using *OpenStreetMap* data are classified as indoor images with *Places CNN*. We suggest that higher building density in urban and suburban areas may mean that higher location accuracy is required to avoid misclassification between indoor and outdoor locations, such that a greater proportion of misclassifications is to be expected. This problem is likely to be exacerbated due to reduced accuracy of GPS location technology in built-up areas. *OpenStreetMap* data can also suffer from lack of positional accuracy and lack of completeness (Haklay, 2010; Zielstra et al., 2013). Urban and suburban areas may be more likely to have buildings that have yet to be added to the *OpenStreetMap* buildings data. Our *OpenStreetMap* data on POIs may also contain a great deal of uncertainty, particularly in urban and suburban areas where there are likely to be a greater number of POIs and thus a higher chance of inaccuracies.

Furthermore, we note that *Scenic-Or-Not* ratings are provided on a 1 km grid square basis. At the same time, urban and suburban LSOAs are likely to be smaller than rural LSOAs: rural LSOAs range from 2 to 67,280 hectares; suburban LSOAs range from 4 to 5,362 hectares; and urban LSOAs range from 1 to 4,804 hectares. Information on the scenicness of urban and suburban areas may therefore be lower in quality, due to a lower number of scenicness ratings per LSOA. Further research will need to be conducted in order to mitigate these factors.

Nonetheless, analysis of crowdsourced data does seem to provide valuable information on how people perceive their everyday environments. Our results suggest that by exploiting data gathered from our everyday interactions with the Internet, scientists and policymakers alike may be able to develop a better understanding of people's subjective experience of the environment in which they live.

Chapter 4
Predicting scenic ratings using deep learning

4.1 Introduction

In Chapter 3, we explored whether the vast quantity of data uploaded to the Internet – in this case, geotagged images uploaded to *Flickr* combined with crowdsourced geographic data from *OpenStreetMap* – can be used to estimate the scenicness of places for which we do not have crowdsourced scenic ratings. We find that models including crowdsourced data from Flickr and *OpenStreetMap* can generate more accurate estimates of scenicness than models that consider only basic census measurements such as population density or whether an area is urban or rural, however the improvement is modest.

Recent advances in computer vision methods, particularly convolutional neural networks (CNNs), provide us with a new method to extract visual information about our environment at a large scale (De Nadai et al., 2016; Dubey et al., 2016). We draw on this ongoing and rapid improvement in computer vision techniques, particularly in convolutional neural networks, to evaluate to what degree of accuracy we can create a CNN to predict the beauty of scenes for which we do not have survey or crowdsourced scenicness data.

In this chapter, we first use images from *Scenic-Or-Not* (introduced in Chapter 3) to train a CNN, and we evaluate its accuracy for predicting scenicness. The *Scenic-Or-Not* images were originally sourced from *Geograph,* an online crowdsourcing project created to collect and reference geographically representative images of each square kilometre of the British Isles. In order to ensure our CNN is versatile, we then evaluate how well it performs on a completely different source of images, *Google Street View,* which contains pictures of the environment around the globe. This test indicates how accurate our CNN might be when used to predict the scenicness of images in a country that does not have data equivalent to the *Geograph* dataset in the UK. Our ultimate aim is to develop the means to generate large-scale data on the scenicness of the environment, in order to enable future research that aims to explore the connection between scenic beauty and various important measures beyond just wellbeing, such as the performance of the local economy, tourism performance, and perhaps levels of residential physical activity. Part of the research reported in this chapter was published in Seresinhe, Preis & Moat (2017).

4.2 Building a deep learning model to predict scenicness

In our first attempt to build a model to predict the scenicness of images, we use data from *Scenic-Or-Not* (as detailed in Chapter 3) to determine how accurately our model is able to predict scenicness. We first build an elastic net model to establish a baseline prediction accuracy. We specifically choose to use an elastic net model as these have been shown to perform well even in situations where there are highly correlated predictors (Zou & Hastie, 2005). We then assess how much we can improve this accuracy with a deep learning model, specially a convolutional neural network. The introduction of convolutional neural networks has lead to dramatic improvements in computer vision tasks, including visual recognition (Donahue et al., 2014; Sharif Razavian et al., 2014), understanding image aesthetics (Tan et al., 2017; Lu et al., 2015), and extracting perceptions of urban neighbourhoods (De Nadai et al., 2016; Dubey et al., 2016). Thus, our hypothesis is that our deep learning model will lead to a far greater prediction accuracy than our elastic net model.

4.2.1 Data and methods

Scenic-Or-Not data

The *Scenic-Or-Not* web game presents users with random geotagged photographs of Great Britain, which visitors can rate on an integer scale 1 – 10, where 10 indicates “very scenic” and 1 indicates “not scenic”. Each image, sourced from *Geograph*, represents a 1 km grid square of Great Britain. See section 3.2 for a full description of the data. For our final analysis, we use 206,171 images in total and hold out 20% of this dataset to test our prediction accuracy.

Extracting scene attributes and place categories from Scenic-Or-Not images

For each *Scenic-Or-Not* image, we use the Places205 AlexNet CNN (Zhou et al., 2014), which has been trained on data from the Scene UNderstanding (SUN) attribute database (Patterson et al., 2014) to extract the probabilities of 102 scene attributes such as “trees” and “flowers”. The SUN attribute database contains 102 discriminative outdoor scene attributes, spanning from materials to activities (e.g. “wire”, “vegetation”, “shopping”). We extract probabilities for scene attributes from the FC7 layer (the penultimate fully-connected layer) of the AlexNet CNN. Table 4.1 lists all the scene attributes used in our analysis.

Table 4.1. 102 Scene UNderstanding (SUN) Scene Attributes.
We use the Places205 AlexNet CNN (Zhou et al., 2014) trained on data from the Scene UNderstanding (SUN) attribute database (Patterson et al., 2014) to extract the probabilities of the 102 listed scene attributes.

sailing/boating	spectating	tiles	glossy
driving	farming	concrete	matte
biking	constructing	metal	sterile
transporting	shopping	paper	moist
sunbathing	medical	wood	dry
touring	working	vinyl	dirty
hiking	using tools	plastic	rusty
climbing	digging	cloth	warm
camping	business	sand	cold
reading	praying	rocky	natural
studying	fencing	dirt soil	man-made
Rtraining	railing	marble	open area
research	wire	glass	semi-enclosed area
diving	railroad	waves	enclosed area
swimming	trees	ocean	far-away horizon
bathing	grass	running water	nohorizon
eating	vegetation	still water	rugged
cleaning	shrubbery	ice	vertical components
socializing	foliage	snow	horizontal components
congregating	leaves	clouds	symmetrical
waiting	flowers	smoke	cluttered
competing	asphalt	fire	scary
sports	pavement	natural light	soothing
exercise	shingles	sunny	stressful
playing	carpet	electric lighting	
gaming	brick	aged	

We use the more recent Places365 CNN (Zhou et al., 2016), trained on the Places2 dataset, a repository of 8 million scene photographs, to extract the probabilities of 365 place category classifications such as “mountain”, “lake natural”, “residential neighbourhood” and “train station platform”. We specifically use the Places365 CNN trained using the 152-layer Residual Network (ResNet152) architecture (He et al., 2016), as this resulted in the best classification accuracy. Table 4.2 lists all the place categories used in our analysis.

Table 4.2. 365 Place Categories.
We use the more recent Places365 CNN (Zhou et al., 2016) trained on the Places2 dataset (a repository of 8 million scene photographs) to extract the probabilities of the 365 listed place category classifications such as “mountain”, “lake natural”, “residential neighbourhood” and “train station platform”. In our elastic net model, we consider only features that have been labelled as outdoor place categories.

Outdoor					
airfield	carrousel	forest path	lake natural	picnic area	stage
alley	castle	forest road	landfill	pier	street
amphitheater	cemetery	formal garden	landing deck	playground	swamp
amusement park	chalet	fountain	lawn	plaza	swimming pool
apartment building	church	garage	library	pond	synagogue
aqueduct	cliff	gas station	lighthouse	porch	temple asia
arch	coast	gazebo exterior	loading dock	promenade	topiary garden
army base	construction site	general store	lock chamber	racecourse	tower
athletic field	corn field	glacier	mansion	raceway	tree farm
badlands	corral	golf course	manufactured home	raft	tree house
balcony exterior	cottage	greenhouse	market	railroad track	trench
balcony interior	courthouse	grotto	marsh	rainforest	tundra
bamboo forest	courtyard	hangar	mausoleum	residential neighborhood	underwater ocean deep
barn	creek	harbor	medina	restaurant patio	valley
barndoor	crevasse	hayfield	moat water	rice paddy	vegetable garden
baseball field	crosswalk	heliport	mosque	river	viaduct
bazaar	dam	highway	motel	rock arch	village
beach	desert sand	hospital	mountain	roof garden	vineyard
beach house	desert vegetation	hot spring	mountain path	rope bridge	volcano
beer garden	desert road	hotel	mountain snowy	ruin	volleyball court
boardwalk	diner	house	museum	runway	water park
boat deck	doorway	hunting lodge	oast house	sandbox	water tower
boathouse	downtown	ice floe	ocean	schoolhouse	waterfall
botanical garden	driveway	ice shelf	office building	shed	watering hole
bridge	embassy	ice skating. rink	oilrig	shopfront	wave
building facade	excavation	iceberg	orchard	ski resort	wheat field
bullring	farm	igloo	pagoda	ski slope	wind farm
bus station	field cultivated	industrial area	palace	sky	windmill
butte	field wild	inn	park	skyscraper	yard
cabin	field road	islet	parking garage	slum	zen garden
campsite	fire escape	japanese garden	parking lot	snowfield	
campus	fire station	junkyard	pasture	soccer field	

canal natural	fishpond	kasbah	patio	stadium baseball	
canal urban	football field	kennel	pavilion	stadium football	
canyon	forest broadleaf	lagoon	phone booth	stadium soccer	
Indoor					
airplane cabin	basement	closet	galley	martial arts gym	server room
airport terminal	basketball court	clothing store	garage	mezzanine	shoe shop
alcove	bathroom	cockpit	general store	movie theater	shopping mall
amusement arcade	bazaar	coffee shop	gift shop	museum	shower
aquarium	beauty salon	computer room	greenhouse	music studio	stable
arcade	bedchamber	conference center	gymnasium	natural history museum	stage
archaelogical excavation	bedroom	conference room	hangar	nursery	staircase
archive	beer hall	corridor	hardware store	nursing home	storage room
arena hockey	berth	delicatessen	home office	office	subway station platform
arena performance	biology laboratory	department store	home theater	office cubicles	supermarket
arena rodeo	bookstore	dining hall	hospital room	operating room	sushi bar
art gallery	booth	dining room	hotel room	orchestra pit	swimming hole
art school	bow window	discotheque	ice cream.parlor	pantry	swimming pool
art studio	bowling alley	dorm room	ice skating.rink	parking garage	television room
artists loft	boxing ring	dressing room	jacuzzi	pet shop	television studio
assembly line	burial chamber	drugstore	jail cell	pharmacy	throne room
atrium public	bus interior	elevator door	jewelry shop	physics laboratory	ticket booth
attic	butchers shop	elevator lobby	kindergarden classroom	pizzeria	toyshop
auditorium	cafeteria	elevator shaft	kitchen	playroom	train interior
auto factory	candy store	engine room	laundromat	pub	train station platform
auto showroom	car interior	entrance hall	lecture room	reception	utility room
bakery shop	catacomb	escalator	legislative chamber	recreation room	veterinarians office
ball pit	chemistry lab	fabric store	library	repair shop	waiting room
ballroom	childs room	fastfood restaurant	living room	restaurant	wet bar
bank vault	church	flea market	lobby	restaurant kitchen	youth hostel
banquet hall	classroom	florist shop	locker room	sauna	
bar	clean room	food court	market	science museum	

Extracting basic characteristics from Scenic-Or-Not images

We also explore the basic characteristics of photographs in our scenic ratings dataset, including their colour composition, saturation, brightness and colour variation. We examine each image from *Scenic-Or-Not* on a per-pixel level, with each pixel allocated to one of eleven colours that constitute the principal colours in the English vocabulary (black, blue, brown, grey, green, orange, pink, purple, red, white, yellow). As colour naming varies from one individual to another (Ratliff, 1976), we draw on crowdsourced data generated through an online survey of 1.5 million participants (Munroe, 2010) to determine to which colour a pixel should be allocated. In this survey, participants were shown an area filled with a random fully-saturated colour on both black and white backgrounds, and asked to name the colour. These responses were then used to create a list of the dominant colour names corresponding to fully saturated RGB (Red, Green, Blue) values. We use this data in order to determine where colour boundaries should be drawn: for example, where “brown” ends and “green” begins. The RGB colours are converted to the HSV (Hue, Saturation, Value) colour space and each pixel is matched to the closest corresponding colour, based on its hue parameter. The nature of the relationship between HSV and RGB space is such that all possible hues are covered by all fully saturated RGB colours. As black, grey and white do not have a defined hue, these colour boundaries were determined based on a combination of the levels of “Saturation” and “Value” (Fig. 4.1).

We measure the saturation of each image by calculating the mean “Saturation” of each pixel in the HSV colour space. We measure the brightness of each image by calculating the mean “Value” of each pixel in the HSV colour space. We measure the colour variation of each image by using k-means clustering to reduce the colour palette of each image to an eight-colour palette. We then compute the mean R, G and B values of the colour palette, and then derive a measure of how much colour variation is in the image by taking the square root of the sum of squares of each palette colour’s R, G and B difference from the mean.

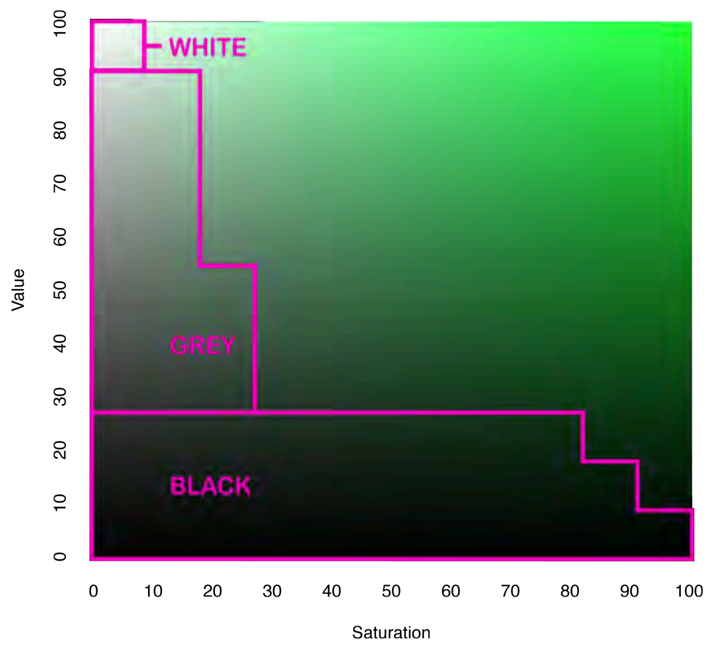


Figure 4.1. Allocating black, grey and white based on value and saturation. Here, the hue has been set to one colour (green) in order to illustrate where the boundaries of black, grey and white are set. At the borders, the colour may appear to be more or less grey, as well as more or less black, depending on the hue, so the boundaries are chosen as a best-fit compromise over the entire range of hue values.

Elastic net model

Elastic net models are a compromise between ridge regression and LASSO (Least Absolute Shrinkage and Selection Operator), both of which are adaptations of the linear regression model, with a penalty parameter in order to avoid overfitting. In order to exploit the information contained in all the photographs in our dataset, we build an elastic net model that considers the following features extracted from the images: basic characteristics such as colour composition, 102 SUN scene attributes, and those Places365 place categories that are labelled as outdoor, of which there are 205. (Note that these 205 outdoor categories from the Places365 CNN differ from the 205 outdoor and indoor categories from the Places205 CNN). In our Elastic Net Model, we use cross validation to learn the alpha parameter of the elastic net (the mix between ridge and lasso) as well as the lambda parameter (the penalty).

Convolutional neural networks (CNNs) and transfer learning

While we anticipate that a CNN model has the potential to perform much better for this task than an elastic net model, creating a CNN that can perform adequately for any computer vision task, such as object detection, typically requires a training dataset comprising millions of images. For example, the CNN that won the 2012

ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) was trained on roughly 1.2 million images and achieves an error rate of only 17.0% when predicting the top five labels for an image (Krizhevsky, Sutskever & Hinton, 2012). As we have limited training data, we use a transfer learning approach (Pan & Yang, 2010) to leverage the knowledge of the pre-trained Places365 CNN (introduced above), as this CNN already performs well for place recognition. Figure 4.2 illustrates the method used for this approach. We fine-tune all the layers of the CNN, already trained on the Places365 database, to predict the scenicness of images. We examine the performance of all four different architectures that have been used to train the Places365 CNN: AlexNet (Krizhevsky, Sutskever & Hinton, 2012), Visual Geometry Group (VGG16) (Simonyan & Zisserman, 2014), GoogLeNet (Szegedy et al., 2015) and ResNet152 (He et al., 2016). For all our experiments, we use the deep learning framework Caffe (Szegedy et al., 2015). For AlexNet, Visual Geometry Group (VGG16) and GoogLeNet, training is performed by stochastic gradient descent (SGD) with mini-batch size 50, a learning rate 0.0001 and momentum 0.9, for 10,000 iterations. For ResNet152, training is performed using a mini-batch size of 10 (due to GPU memory constraints) for 50,000 iterations, to ensure all four networks were exposed to the same amount of images.

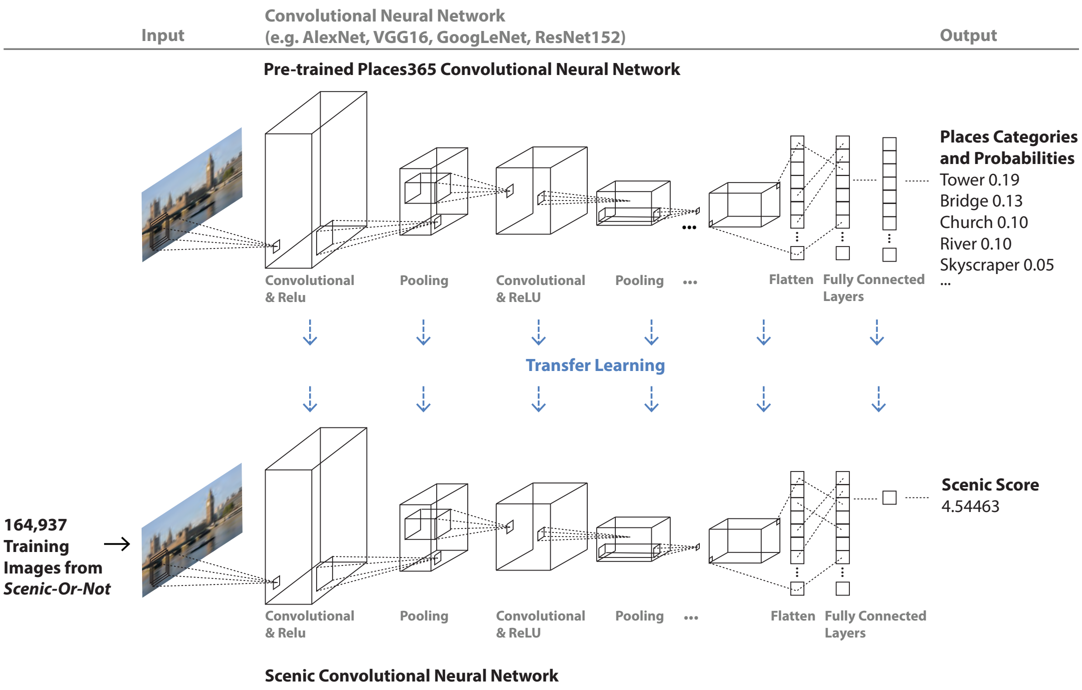


Figure 4.2. Using transfer learning to predict scenicness.
Here, we provide an abstract illustration of the CNN architecture and our approach. As we have limited training data, we use a transfer learning approach (Pan & Yang, 2010) to leverage the knowledge of the Places365 CNN. We modify the final layer of our convolutional neural network to predict scenic scores rather than the probabilities of place

categories. Image © Copyright Philip Halling. Copyright of the image is retained by the photographer. Images are licensed for reuse under the Creative Commons Attribution-Share Alike 2.0 Generic License. To view a copy of this licence, visit http://creativecommons.org/licenses/by-sa/2.0/. Figure adapted from Mathworks Convolutional Neural Networks webpage figure at https://uk.mathworks.com/discovery/convolutional-neural-network.html.

4.2.2 Results

Table 4.3 compares the results for both the elastic net and all the fine-tuned CNN models. Our performance measure is the Kendall's Rank correlation between the predicted scenic scores and the actual scenic scores. With our elastic net model, we achieve a performance score of 0.544 for all images and 0.445 for urban built-up images. The Scenic-Or-Not CNN trained using the VGG16 convolutional neural network architecture delivers the best performance for all images, achieving a performance score of 0.658 for all images and 0.590 for urban built-up images, measured using Kendall's rank correlation. The performance of the slightly deeper GoogLeNet and the much deeper ResNet152 models are similar. Further experiments could be carried out in the future to determine if the deeper networks can be made to perform better, perhaps by varying training parameters (for example, by choosing different learning rates or different optimisation techniques). However it might be the case that for this task, the deeper networks may be more prone to overfitting, and thus may not generalise well (Kabkab, Hand & Chellappa, 2016). Further experiments would be required to conclusively state which network might be best suited for prediction of scene aesthetics.

Table 4.3. Scenic-Or-Not CNN Prediction Results.
We check to what degree we can predict the beauty of scenes for new places for which we do not have survey or crowdsourced scenicness data. Our first model is an elastic net model to predict the scenicness of images. Our second model is a convolutional neural network fine-tuned on the Places365 CNN to predict the scenicness of images. We check the performance on four different convolutional neural network architectures that have been used to train the Places365CNN: AlexNet, Visual Geometry Group (VGG16), GoogleNet and ResNet152. We hold out a 20% test set to check our prediction accuracy. We calculate a performance measure using the Kendall Rank correlation between the predicted scenic scores and the actual scenic scores. All four Scenic CNNs outperform the elastic net model in both of our datasets, with all *Scenic-Or-Not* images, and also with only Urban Built-up *Scenic-Or-Not* images. The Scenic CNN trained using the VGG16 convolutional neural network architecture delivers the best performance overall.

	Elastic net	**Scenic CNN**			
		AlexNet	**VGG16**	**GoogleNet**	**ResNet152**
All	0.544	0.627	0.658	0.653	0.654
Urban Built-up	0.445	0.553	0.590	0.590	0.567

4.3 Predicting scenicness at a higher resolution

Our *Scenic-Or-Not* database contains only one image per 1 km^2 grid square, and only in Great Britain. Generating scenic ratings at a higher resolution might help us in studies where we want to understand the connection between scenicness and wellbeing in areas where scenicness varies considerably, such as high-density urban areas, or if we want to track how scenicness might change over time. We check how well our Scenic-Or-Not CNN performs in London – an area for which we do not have data at a high resolution from *Scenic-Or-Not* – by predicting scenic ratings of images from two sources: *Geograph* and *Google Street View.* We also retrain our Scenic-Or-Not CNN on *Google Street View* images to see if we can improve performance on this new set of images.

4.3.1 Data and methods

Geograph images at high resolution for London

Geograph (http://www.geograph.org.uk) is an online documentation project encouraging users to submit geographically representative photographs of Great Britain. The *Scenic-Or-Not* images were originally sourced from *Geograph.* To see how well our Scenic-Or-Not CNN picks up scenic areas around London, we use all images uploaded to *Geograph* that we can locate in London and that we have identified as having been taken outdoors; this results in 243,339 images.

We use the Places CNN (Zhou et al., 2014) to determine whether any of the images in our above dataset have been taken indoors, and exclude these images. The labels of the top five predicted place categories can be used to classify images as depicting indoor or outdoor locations with more than 95% accuracy (Zhou et al., 2014).

Google Street View images

Google Street View is a *Google Maps* feature that displays panoramas of stitched photographs of streets. Most photographs are taken by *Street View* cars, but hard-to-access locations are sometimes photographed using other equipment such as the *Street View Trekker*, a wearable backpack outfitted with a camera system. We create two separate databases of *Google Street View* images: (1) a small database to test our prediction accuracy, as the *Google Street View* images are remarkably different from our *Scenic-or-Not* images, and (2) a much larger database to see how well we can predict scenic areas around London and to see if we can determine changes in scenicness over time.

Google Street View images to test prediction accuracy

In order to test how well our Scenic-Or-Not CNN performs on *Google Street View* images, we need to gather ground truth data on the scenic ratings of this new image dataset. We use the *Google Street View API* to randomly sample four images per Inner London Lower Layer Super Output Areas (LSOAs). LSOAs are defined by the Office for National Statistics for statistical analyses. LSOAs are geographic areas ranging from 0.018 to 684 square km, containing between 983 and 8,300 residents (1,500 on average). We choose LSOAs from the following local authority districts of Inner London: Camden, Greenwich, Hackney, Hammersmith and Fulham, Islington, Royal Borough of Kensington and Chelsea, Lambeth, Lewisham, Southwark, Tower Hamlets, Wandsworth, Westminster, and City of London. We use systematic unaligned sampling to generate the coordinates of the images, whereby the sample space (i.e. the entire LSOA) is split into four equal-sized sub-areas, and a random [x, y] coordinate is generated for each sub-area.

Following a similar procedure to *Scenic-Or-Not,* we present our images in a web interface to be rated on a scale of 1-10. Figure 4.3 shows the interface for *Scenic London*. The respondents to our exercise were mainly sourced from a massive open online course (MOOC) running on the online learning platform *FutureLearn*. In this exercise, participants were asked to rate at least 20 images. We gathered 34,955 ratings for 6,948 images from 15 June 2017 to 12 September 2017. We again hold out 20% of our data to test prediction accuracy.

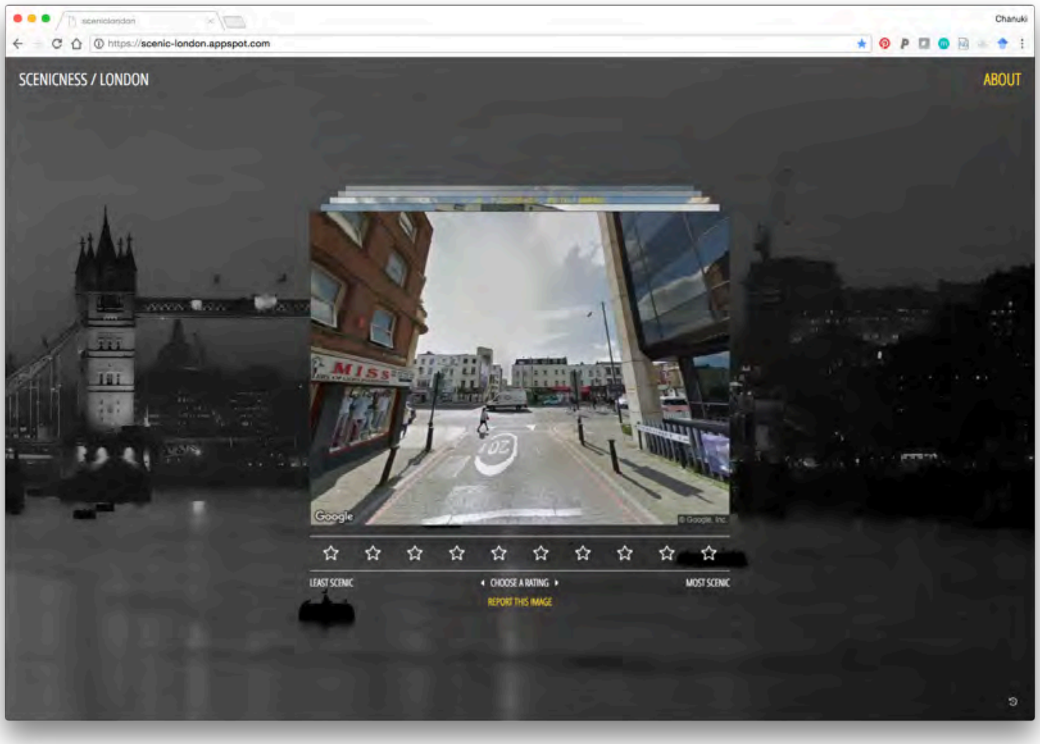


Figure 4.3. The *Scenic London* visiting screen.
Screenshot of interface to gather votes for *Google Street View* images of inner London. Image @ 2017 Google**.**

Google Street View images at high resolution for London

We use the Python module *Streetview* (Letchford, 2016) to locate images on a 100-square-meter-resolution grid across all of London: one image per grid square taken in 2008-2009 and another taken in 2014-2015. Each point on the grid is allocated a unique "location ID". For each location ID, we search for pairs of images that are maximum 5 meters apart. If there is no match across time periods, or no picture available for a location ID, we do not consider any pictures for that location. This results in 506,854 pairs of images, where 41,961 pairs are in the exact same location.

4.3.2 Results

Geograph images

We first see how well our Scenic-Or-Not CNN picks up scenic areas around London using images sourced from *Geograph.* As the *Scenic-Or-Not* images are originally sourced from *Geograph,* we anticipate good performance from our CNN for the full *Geograph* dataset. Figure 4.4a demonstrates that parks known for their scenery, such as Hampstead Heath and Richmond Park, have large clusters of scenic imagery. We also see that areas around large bodies of water such as the

Thames also seem to contain the most scenic imagery. The most unscenic images seem to be located in the city centre. However, a close-up view reveals clusters of highly scenic imagery in attractive built-up areas, such as Trafalgar Square. An examination of the photos predicted to be scenic indicates that while our Scenic-Or-Not CNN predicts high ratings for images containing primarily natural elements, images of man-made elements, particularly historical architecture around the city, including Big Ben and the Tower of London, are also predicted to be scenic (Fig. 4.4b). While our Scenic-Or-Not CNN in general predicts low ratings for images containing primarily man-made features, images with a restricted view as well as those containing large areas of drab or unmaintained green space are also rated as unscenic (Fig. 4.4c).

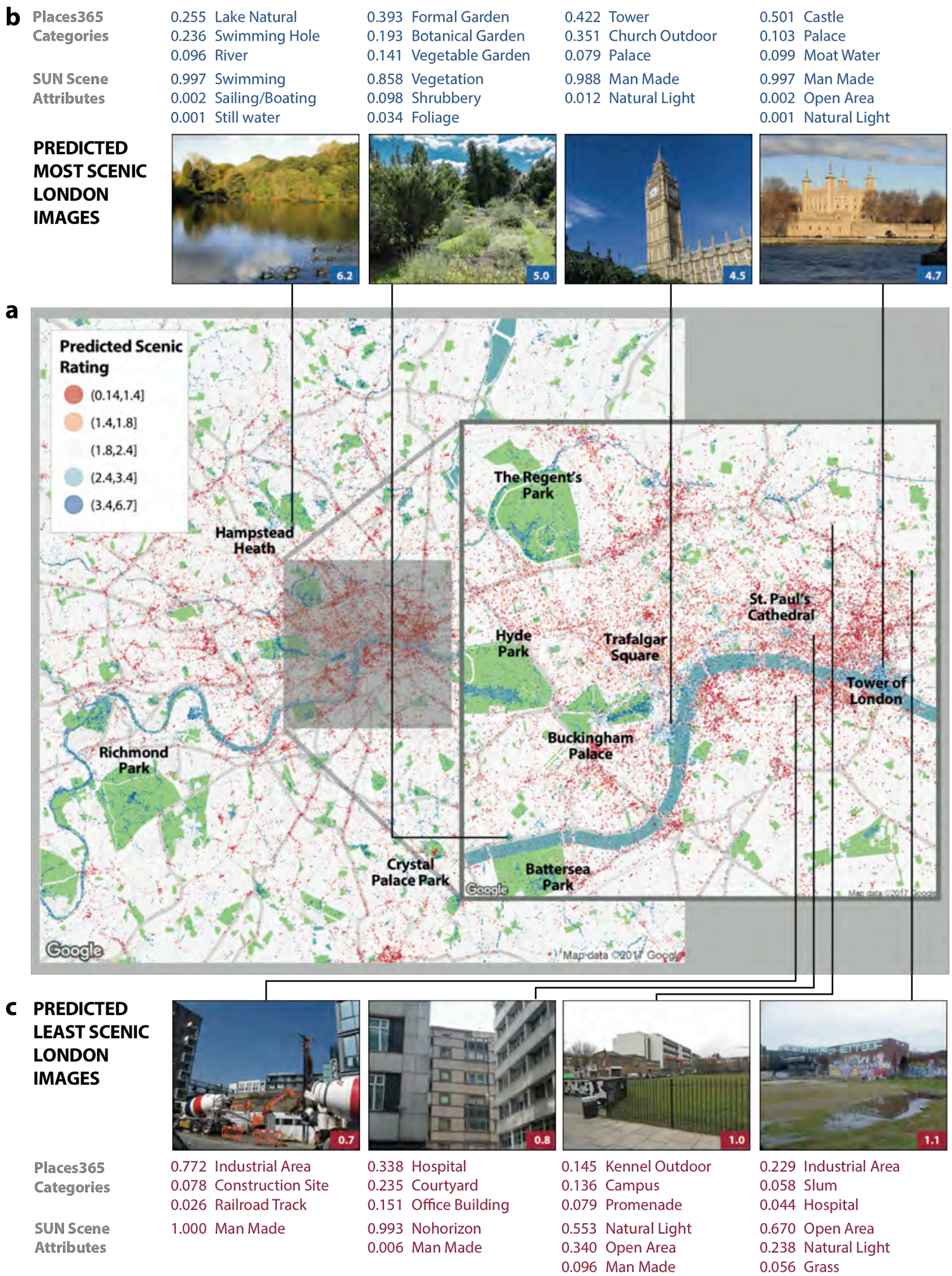


Figure 4.4. Predictions of scenic ratings for London images with our Scenic-Or-Not CNN.
With our Scenic-Or-Not CNN, we predict the scenicness of pictures of London uploaded to Geograph (http://www.geograph.org.uk), an online project that collects geographically representative photographs of Great Britain and Ireland. Note that only those categories and features given a probability of 0.001 or higher have been included in the figure. **(a)** Examining the estimates of how scenic images around London are, we immediately notice that parks known for their attractive scenery such as Hampstead Heath and Richmond Park

have large clusters of images rated as scenic. The city centre appears to be largely unscenic, although a close-up view reveals clusters of scenic images in built-up areas. **(b)** A sample of the top 5% of the photos predicted to be scenic indicates that our Scenic CNN mostly predicts high ratings for images containing primarily natural elements. However, we also see that images containing primarily man-made objects can also be estimated as scenic. **(c)** A sample of the bottom 5% of the photos predicted as scenic indicates that our CNN predicts low ratings for images containing primarily man-made features. Images with a restricted view can also be rated as unscenic. However, images containing large areas of green space also tend to be rated low if they are largely flat and uninteresting or unmaintained. Owing to the different shapes of the photographs, some images have been cropped to aid presentation in this figure. Photographers of scenic images: © Copyright Stephen McKay, © Copyright Christine Matthews, © Copyright Christine Matthews, © Copyright Roger Davies; Photographers of unscenic images: © Copyright Stephen Craven, © Copyright Robert Lamb, © Copyright John Salmon, © Copyright Marathon. Copyright of the images is retained by the photographers. Images are licensed for reuse under the Creative Commons Attribution-Share Alike 2.0 Generic License. To view a copy of this licence, visit http://creativecommons.org/licenses/by-sa/2.0/. Map created using R package "ggmap" (Kahle & Wickham, 2013). Map data © 2017 Google.

Google Street View images

We now see how well our Scenic-Or-Not CNN picks up scenic areas around London from *Google Street View* images. Such a data source has the advantage of being comprehensive, with many more images available per unit area compared to *Scenic-Or-Not*, as well as historical images at each location. However, *Google Street View* images have some important fundamental differences from *Scenic-Or-Not / Geograph* images: they typically have a wider angle of view, and can often contain image artefacts such as blurred areas. Therefore, using our current Scenic-Or-Not CNN, we anticipate that we might not be able to predict scenicness for *Google Street View* images with as high an accuracy as for *Geograph* images. For this reason, we create a separate test set of *Google Street View* images to first test how accurately we can predict the scenicness of these images.

We again hold out 20% of our *Google Street View* images to test prediction accuracy. Without further training of the Scenic-Or-Not CNN, we achieve a performance score of 0.286. This is much lower than for the original *Scenic-Or-Not* test set, for which the Scenic-Or-Not CNN achieved 0.658 for all images and 0.590 for urban built-up images. We therefore leverage a similar transfer learning approach as before to further train the Scenic-Or-Not CNN on the training set of *Google Street View* images to see if we can improve performance.

We further train the previous Scenic-Or-Not CNNs using all four different convolutional neural network architectures (AlexNet, VGG16, GoogLeNet, ResNet152). We follow the same method as before, but now train over fewer iterations, as we do not have as many images in our training set (5,500 *Google Street View* images compared to 160,000 *Scenic-Or-Not* images). We achieve the best performance with the Scenic-Or-Not CNN trained on GoogLeNet (from now on referred to as Street-View-Scenic CNN) for 2000 iterations, which exhibited a performance score of 0.435. While the model has improved remarkably, from 0.286 to 0.435 on *Google Street View* images, the performance score of the Street-View-Scenic CNN is still much lower than what we were able to achieve with the Scenic-Or-Not CNN on *Scenic-Or-Not* images. We reflect on the reasons why this might be the case in the discussion section.

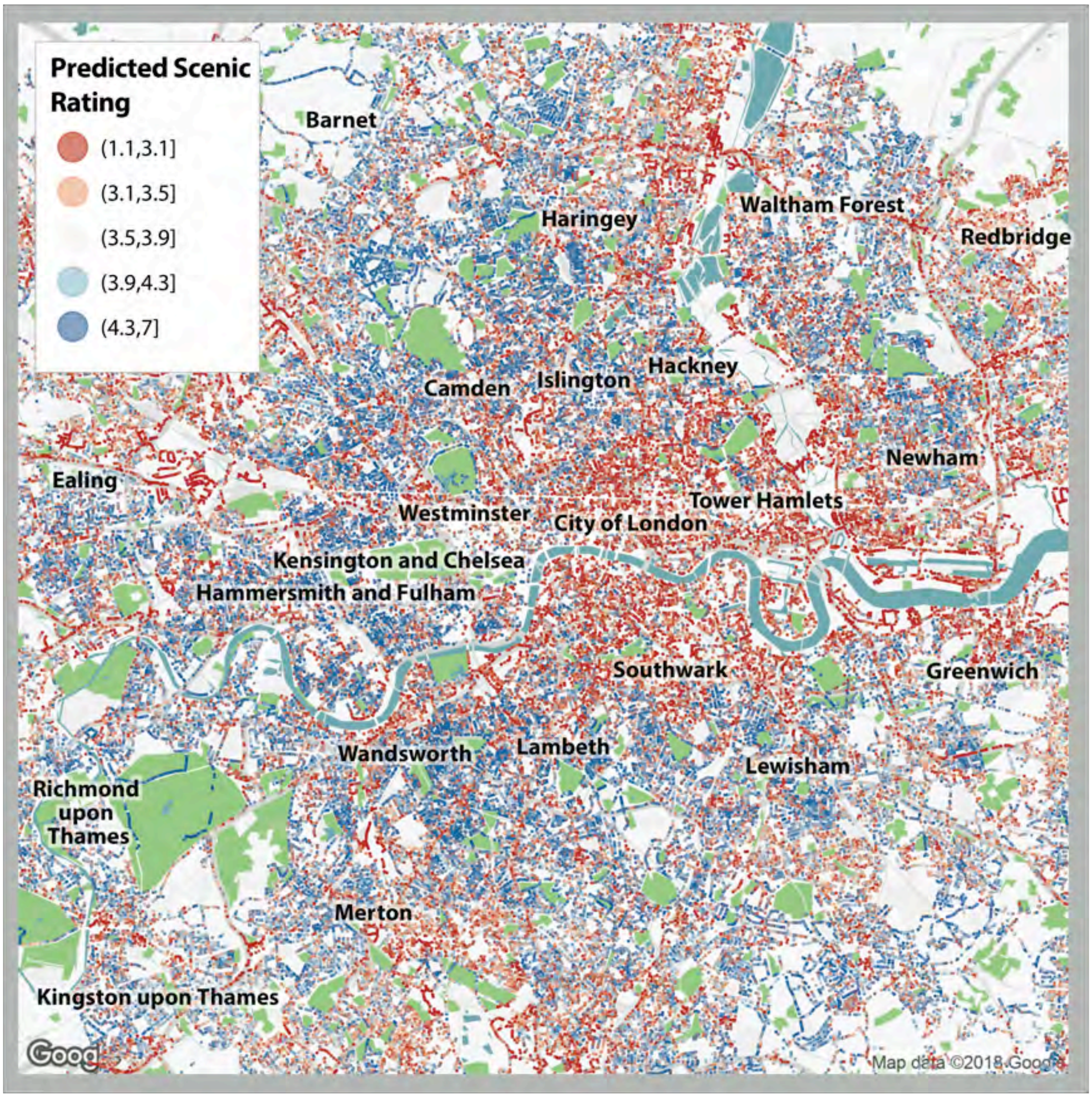


Figure 4.5. Predictions of scenic ratings of *Google Street View* images for 2015.
With our Street-View-Scenic CNN, we predict the scenicness of pictures of London accessed from *Google Street View*. We are now able to estimate where scenic places are around London at a much higher density. As expected, images found on park paths, such as Richmond Park, are rated as highly scenic. We also see that many images on streets can also be rated as scenic. Overall, the majority of the streets in Central and East London are not as scenic as streets in North, South and West London. Map created using R package "ggmap" (Kahle & Wickham, 2013). Map data © 2018 Google.

We now investigate how our new Street-View-Scenic CNN performs on a more comprehensive set of *Google Street View* images of Greater London, using the 506,854 matched pairs of images retrieved for 2008 and 2015. We find some similar patterns to our *Geograph* images. Figure 4.5 depicts ratings for the images retrieved for 2015, and demonstrates that images found on park paths are rated as highly scenic. As we now have far more images on streets, we also now see a plethora of images on streets rated as scenic; these images might represent streets abundant in greenery or beautiful architecture. We also see clearly that the majority of the areas in Central and East London are not as scenic as areas in North, South and West London.

We also map out the changes in scenic ratings from 2008/2009 to 2014/2015. From visual inspection, it appears that areas in outer London have become more unscenic, while areas in central and east London have become more scenic. However, the data reveals that the changes in scenicness are relatively small, falling between -2.1 to +2.1. We therefore investigate what factors may be driving these changes in scenic ratings, to help understand whether these changes represent a signal of value, or merely artefacts in the *Google Street View* dataset.

We select a number of images for which changes in estimated scenic rating between 2008/2009 and 2014/2015 were particularly high (defined as differences in scenicness in the third quartile and above). We find that the changes are sometimes driven by actual changes to the design of the street, such as an unsightly building being removed to create a park (Fig. 4.7a) as well as changes to the design of the architecture on the street (Fig. 4.7b,c,d). However, changes can also be temporary, such as a vehicle obstructing the view (Fig. 4.7e), construction (although construction can sometimes continue for years) (Fig. 4.7f), the season and weather (Fig. 4.7g); or the camera's position itself could be slightly different, therefore including different elements of the building in the image (Fig. 4.7h). Some of these changes might be easy to exclude from the dataset, such as camera position and seasonality, as these can be identified via the metadata related to the image. However, changes such as a vehicle appearing in the image, or construction, would potentially require an additional image content analysis before being able to exclude them from the dataset.

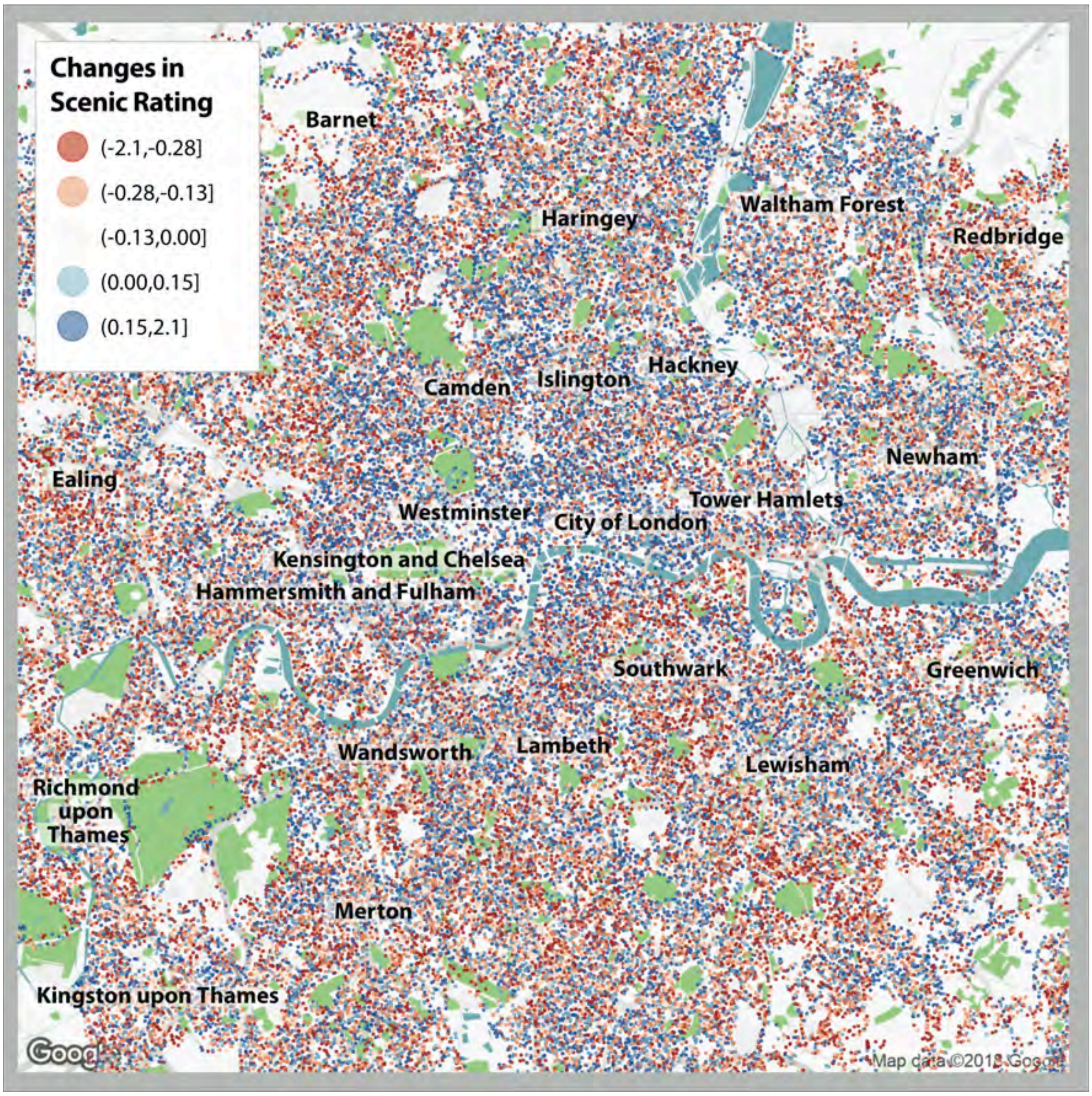


Figure 4.6. Changes in scenic predictions from 2008/2009 to 2014/2015.
With our Street-View-Scenic CNN, we predict the scenicness of pictures of London for 2008/2009 and 2014/2015 and calculate the differences. Map created using R package "ggmap" (Kahle & Wickham, 2013). Map data © 2017 Google. It appears that areas in outer London have become more unscenic, while areas in central and east London have become more scenic.

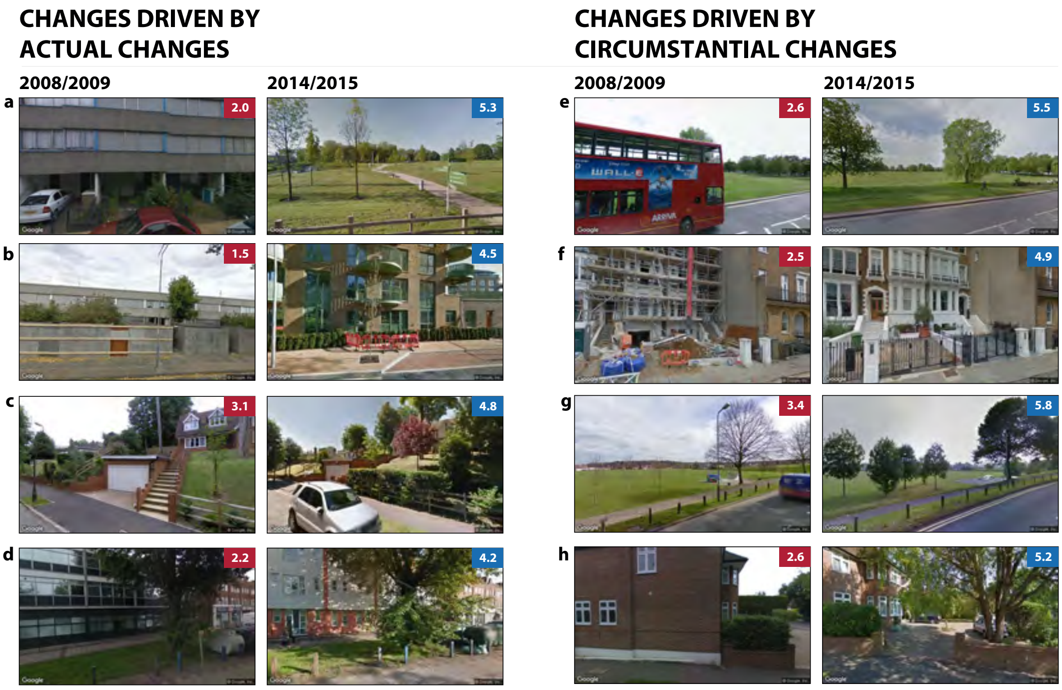


Figure 4.7. Changes in scenic ratings for images in the same location (maximum 5m apart) from 2008/2009 to 2014/15.
We find that the changes in scenic ratings are sometimes driven by actual changes to the design of the street, such as a new park or new design of a building (a-d). However, changes can also be temporary, such as a vehicle obstructing the view (e), construction (f), season and weather (g) or the camera's position (h). Images have been retrieved via the Google Street View API. Images @ 2018 Google**.**

4.4 Discussion

Recent advances in computer vision, particularly the development of CNNs, are allowing us to extract insights from images at a far greater speed and accuracy than ever before. We explore to what level of accuracy we can create a CNN model to predict the beauty of scenes for which we either do not have crowdsourced scenic ratings, or for which we require scenic ratings at a higher resolution. We use a transfer learning approach and modify the existing Places365 CNN in order to create new CNNs to predict the scenicness of images. We achieve the best performance with our Scenic-Or-Not CNN trained using images from the *Scenic-Or-Not* dataset*,* which are images originally sourced from *Geograph,* using the VGG16 convolutional neural network architecture (performance scores are 0.658 for all images and 0.590 for our urban built-up images).

We also explore how our Scenic-Or-Not CNN performs on images from another source, *Google Street View,* as this allows us to gather a far more comprehensive dataset of images for future research. Our original Scenic-Or-Not CNN does not perform as well on these images, achieving a performance score of only 0.286.

However, further training of this CNN using *Google Street View* images improves our performance score to 0.435 (using the *GoogLeNet* neural network architecture). We suggest possible reasons why the accuracy for *Google Street View* images might still be lower than the accuracy for *Geograph* images*. Google Street View* images are often of a lower quality than Geograph images, because *Google Street View* images are often composites that contain image artefacts such as blurred areas. Furthermore, the CNN's knowledge is based on training using several million images that have primarily been sourced via search engines (*Google Images, Bing Images, and Flickr*) rather than composite images from *Google Street View*. Thus, the CNN's training is largely based on images that might be not have been shot in the wide angle of view common to *Google Street View* images.

We present our predictions for images in London from both our scenic CNNs (our Scenic-Or-Not CNN and our Street-View-Scenic CNN), and find that they are broadly in line with intuition. Our Scenic-Or-Not CNN predicts high ratings for images containing primarily natural elements, such as those located in London parks known for their attractive scenery, such as Hampstead and Richmond Park, and also predicts high scenic ratings for beautiful buildings, such as the iconic Big Ben and the Tower of London. The Street-View-Scenic CNN also picks up on paths in parks as being Scenic. Interestingly, this CNN seems to find areas in north, south and west London more beautiful compared to central and east London.

We also explore to what degree we can track changes in scenicness over time. Initial inspection of the data suggests that outer areas of London may have become less scenic while areas in central and east London have become more scenic, but the changes in scenicness are small. Further analysis would be required to ascertain to what extent the measured changes represent actual changes to the design of areas in London, or circumstantial changes such as differences in weather, obstruction of views, or temporary construction.

Observing dramatic changes to areas in London using *Google Street View* imagery is also challenging due to the fact that some of the biggest changes are often focused on very compact areas. For example, over the last ten years, the regeneration of the Lower Lea Valley area in East London for the 2012 Olympics and the redevelopment of the Kings Cross area next to the St. Pancras Eurostar station have made remarkable changes to London, but each in its own small area. Thus, in order to track changes in scenicness over time, a far more comprehensive set of images, at an even higher resolution than already gathered, may be needed, including ones taken in public outdoor areas inaccessible to cars. For example, Granary Square in Kings Cross is a beautiful pedestrianised public space featuring choreographed water fountains. Gaining imagery of such areas may soon be possible thanks to Google's increasing use of *Street View* cameras on backpacks, scooters and tricycles to augment their image database to cover new types of locations.

Nonetheless, analyses using convolutional neural networks have helped us to dramatically improve our models to estimate the scenicness of our environment. Our research shows that beauty – once though to be in the eye of the beholder and thus an area of investigation impenetrable by computers – can in fact be decoded by computer algorithms. We argue that the ability to estimate scenicness at large scale and at speed using neural networks opens up new avenues for future social science research to investigate the connection between the beauty of the environment and various aspects of human life, from our wellbeing to the economic prosperity of a city.

SECTION II
What is the connection between scenicness and wellbeing?

We explore the connection between beautiful scenery and different types of wellbeing. We specifically investigate the connection between scenicness and two different measures of wellbeing: (1) experienced wellbeing, as measured though happiness ratings submitted via the mobile phone app *Mappiness*, and (2) evaluative wellbeing, specifically life satisfaction and mental distress, as measured by responses to the annual UK Household Longitudinal Study, *Understanding Society*. Evidence of a quantitative link between the aesthetics of the environment and happiness could inform public policy and the types of investments we want to make to improve human wellbeing.

Chapter 5
Scenicness and experienced wellbeing: An analysis using data from the Mappiness mobile phone app

5.1 Introduction

Areas of great natural beauty have long been considered to be locations in which one might hope to feel a greater sense of happiness. What characteristics of such environments might be driving such an effect? Is it simply the overwhelming presence of nature, or might the beauty of these environments be crucial? If aesthetics play a key role, might this apply in built-up environments too, where policymakers, urban planners, property developers and architects can affect the design of the places we experience, and potentially therefore our everyday happiness?

The relationship between the environment and subjective wellbeing – commonly known as happiness – has been the subject of much scientific research (Bratman et al., 2015a; Bratman et al., 2015b; Hartig et al., 2003; MacKerron & Mourato, 2013; van den Berg et al., 2010; White et al., 2013a; for a full literature review, see Chapter 2) as well as parliamentary briefings (Parliamentary Office of Science and Technology, 2016). Experimental and survey-based studies have produced an array of results suggesting that natural habitats are associated with greater happiness, a result usually explained with reference to the *'biophilia hypothesis'*, which suggests that evolutionary pressures have led to a human preference for a connection with nature (Kellert & Wilson, 1995). However, to date, researchers in this domain have had to contend with considerable limitations in measuring happiness levels as humans experience different environments (Diener et al., 1999) as well as in measuring the aesthetics of those different environments.

Could the aesthetics of an environment therefore have a crucial effect on happiness that studies to date have not been able to capture? We measure happiness using a novel large-scale dataset on everyday happiness ratings, *Mappiness*, an Apple iOS smartphone app that allows users throughout the UK to track their happiness (MacKerron & Mourato, 2013). The *Mappiness* app builds on the Experience Sampling Method (ESM), where participants are asked to use a diary to record details of their wellbeing and current situation at prespecified times of the day (Hektner, Schmidt & Csikszentmihalyi, 2007; Shiffman, Stone & Hufford, 2008). The use of a smartphone app to poll participants allows MacKerron and Mourato (2013) to scale this methodology to tens of thousands of participants, as it reduces the prohibitively high burden of the original diary-based method (Kahneman et al., 2004). Crucially, the smartphone app is also able to use GPS to automatically record the location of a participant when they respond to the survey.

Combining the *Mappiness* ratings with our *Scenic-Or-Not* dataset (introduced in Chapter 3) gives us the unique opportunity to discover whether individuals encountering more scenic environments during their everyday life experience greater levels of happiness. We also investigate if such a relationship holds even in built-up environments, rather than natural habitats, even after taking other environmental measures such as green space into account.

5.2 Data and methods

Scenic ratings

We measure scenicness using crowdsourced scenic ratings from *Scenic-Or-Not* (as detailed in Chapter 3). *Scenic-Or-Not* presents users with random geotagged photographs of Great Britain, which visitors can rate on an integer scale 1 – 10, where 10 indicates "very scenic" and 1 indicates "not scenic". The *Scenic-Or-Not* database has over 217,000 images, sourced from *Geograph*, covering 92.5% of the 234,429 land mass 1 km grid squares of Great Britain. To date, over 1.5 million ratings have been submitted. We use the mean rating of images that have been rated at least three times, and aggregate these ratings at the level of Lower Layer Super Output Area (LSOA). LSOAs are areas defined by the Office for National Statistics for statistical analyses that have a mean population size of around 1,600 and an area of between 0.018 square km to 684 square km.

In order to ensure scenicness ratings are easily comparable to other dummy variables included in our analysis, we rescale the scenicness ratings to 0 to 1 prior to aggregating scenicness measurements on an LSOA basis. After scaling and aggregating scenic ratings per LSOA, the range of scenic ratings is 0.00 to 0.78. In other words, no LSOA has a perfect score of 1. For all of England – the region we use in our final analysis – we have 929,125 votes for 129,056 images, which gives us ratings for 16,907 LSOAs out of the 32,482 LSOAs in England. Following combination with the *Mappiness* dataset as described below, our final scenicness ratings dataset contains 858,773 votes for 119,377 images, covering 14,228 LSOAs.

Mappiness data

We use individual reports of momentary happiness from *Mappiness* (MacKerron & Mourato, 2013) in order to better understand how scenic areas can affect people's wellbeing (Fig. 5.1).

Figure 5.1. *Mappiness* screens.
Mappiness is a pioneering large-scale ESM study that collects UK-wide data via an Apple iOS app (MacKerron & Mourato, 2013).

In the *Mappiness* app, participants choose how often and during which time periods they should be polled; participants are then asked to report their wellbeing at random moments during these times. Participants also respond to questions such as whether they are alone or with someone else, their current location (such as home, work, indoors or outdoors) and what activities they are taking part in (Tab. 5.1). At the time of polling, the app uses the location services of the phone to determine and record the current location of the participant. Figure 5.2 depicts how happiness ratings from the *Mappiness* app vary over time.

We consider a response to be valid only if the start time for the response is within 60 minutes of the most recent prompt by the iOS app, and the questionnaire is completed within 5 minutes. We only include responses that have a device-reported GPS location accuracy of +/- 250m or better, and where the participant has reported that they are either "outdoors" or "in a vehicle". We further exclude measurements collected in LSOAs where no *Scenic-Or-Not* image falls. The resulting dataset constitutes 138,407 measurements of momentary happiness, gathered from 15,444 users between June 2010 and June 2013, covering 14,228 LSOAs out of the 32,482 LSOAs in England. The users report a median household income of approximately GBP £48,000, with a mean age of 35, and a female-to-male ratio of 48:52.

Table 5.1. Mappiness activities.
The table below lists all the *Mappiness* activities that respondents can choose. All the activities are included as control variables in our analysis.

Working, studying	Texting, email, social media
In a meeting, seminar, class	Browsing the Internet
Travelling, commuting	Watching TV, film
Cooking, preparing food	Listening to music
Housework, chores, DIY	Listening to speech/podcast
Admin, finances, organising	Reading
Shopping, errands	Theatre, dance, concert
Waiting, queueing	Exhibition, museum, library
Childcare, playing with children	Match, sporting event
Pet care, playing with pets	Walking, hiking
Care or help for adults	Sports, running, exercise
Sleeping, resting, relaxing	Gardening, allotment
Sick in bed	Birdwatching, nature watching
Meditating, religious activities	Hunting, fishing
Washing, dressing, grooming	Computer games, iPhone games
Intimacy, making love	Other games, puzzles
Talking, chatting, socialising	Gambling, betting
Eating, snacking	Hobbies, arts, crafts
Drinking tea/coffee	Singing, performing
Drinking alcohol	Something else (version < 1.0.2)
Smoking	Something else (version >= 1.0.2)

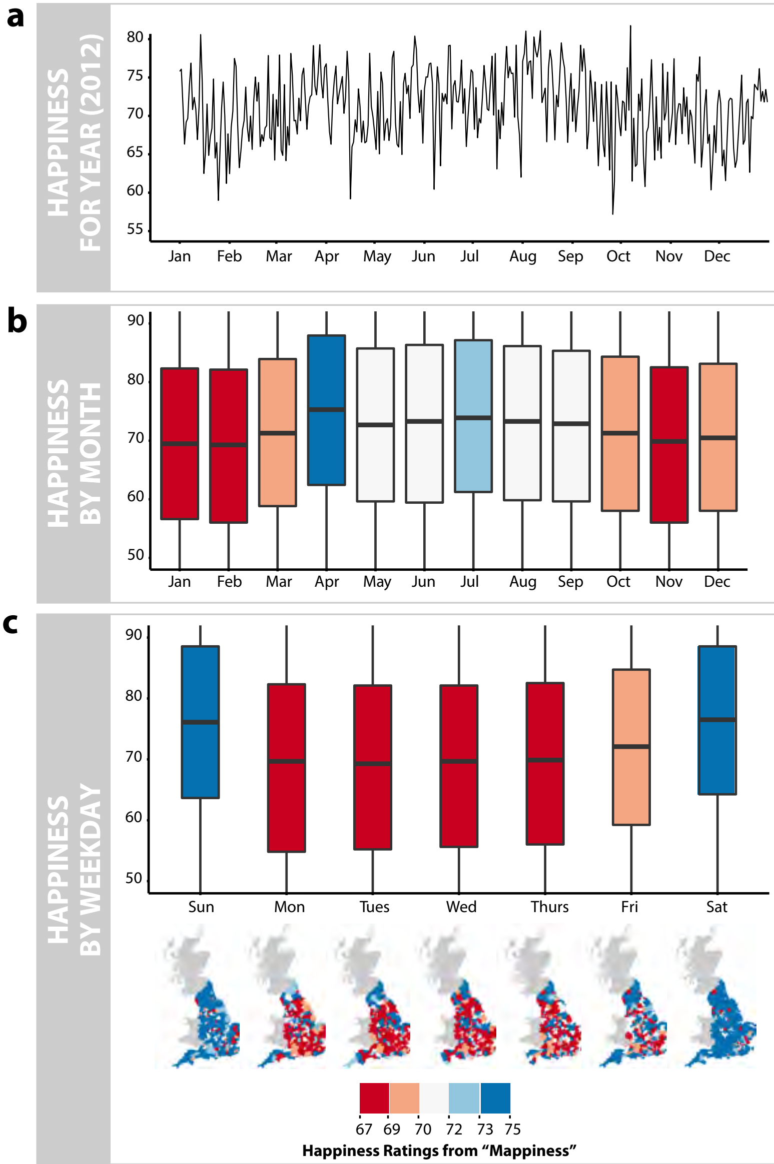


Figure 5.2. Measuring happiness with data from the Apple iOS app *Mappiness.*
(a) Here we show how happiness varies over the year 2012. Trends and oscillations in the measurements suggest that happiness seems to vary depending on factors such as the month or day of the week. (b) We aggregate happiness ratings for all months. Visual inspection suggests that people tend to be less happy during the winter months. (c) Aggregation of happiness ratings by the day of the week shows that people are happiest at the weekends. Location data from *Mappiness* also allows us to visualise how happiness ratings might vary geographically. Across all parts of the figure, colour coding is based on breaks of equal intervals of aggregated weekly happiness ratings.

Fixed effects model

In order to determine how characteristics of the environment relate to changes in individuals' reported happiness levels, we use a fixed effects analytic approach, of the style commonly used in panel data analysis. We choose this approach as the fixed effects model helps us capture possible effects of characteristics of an individual that do not change across time, such as personality traits and gender, which may correlate both with our outcome variable, happiness, and the other explanatory variables in our model (Wooldridge, 2009). In this way, we account for potential effects of individual characteristics on subjective wellbeing (Diener et al., 1999).

People may visit scenic environments with family or friends, when the weather is particularly good, when deciding to take a break in the rolling countryside, or simply for some exercise. As all these factors themselves can contribute to people's happiness, we include a variety of control variables in our model, specifically: companionship, activities (such as walking, sports or gardening) and weather conditions. We also consider the time of day, separately for Monday to Friday or weekends and bank holidays. To account for the fact that usage of the *Mappiness* app may itself affect happiness levels, we control for the number of previous responses by the same participant. We note that *Mappiness* measurements drawn from the same individual or same LSOA are unlikely to be independent. In order to ensure that such dependencies are accounted for in our statistical analysis, we cluster our standard errors on both the individual and LSOA level.

Our basic fixed effects model for estimating happiness in scenic environments is therefore as follows:

$$H_{ilt} = \alpha_i + \beta_s' s_l + \beta_p' p_{it} + \beta_r' r_{lt} + \beta_q' q_l + \epsilon_{ilt}$$

where H_{ilt} $\mathrm{H_{ilt}}$ is an individual's self-rated happiness, scaled from 0 ("not at all happy") to 100 ("extremely happy") at time t and location l; α_i is the unobserved individual-specific constant, $\mathrm{s_l}$ is the scenic rating of the LSOA l; p is a set of individual context control variables including companionship, activity; r is a set of time-variant weather control variables applying to a particular location, such as wind speed, cloud cover and temperature; and q is a set of environmental control variables that do not vary through time, such as percentage of green space, whether a setting is natural or built-up, whether an area is urban, suburban or rural, and the income of local inhabitants.

Akaike weights (AICw)

In order to determine which model best captures variance in the data on happiness, we calculate the Akaike weights of the models (AICws), following the method proposed by Wagenmakers and Farrell (2004). We derive AICws by first identifying the model with the lowest AIC. For each model, we then calculate an AIC difference, by determining the difference between the lowest AIC and the model's

AIC. We next determine the relative likelihood of each model. To determine the AICws, we normalise these likelihoods, such that across all models they sum to 1. The resulting AICws can be interpreted as the probability of each model, given the data.

Weather data

Data on weather conditions has been taken from the Met Office Integrated Data Archive System (MIDAS) database (Met Office, 2006a; Met Office 2006b). In our analysis, we control for potential effects on happiness of wind speed, cloud cover, visibility, temperature, hours of daily sunshine and rain.

Green land cover data

Data on green space per LSOA has been taken from the Generalised Land Use Database Statistics for England 2005 (Department for Communities and Local Government, 2007).

Urban, suburban and rural classifications

"Urban", "suburban" and "rural" areas are defined using data from the 2011 Rural-Urban Classification (Office for National Statistics, 2013). We define "urban" LSOAs to be LSOAs in the category "Urban Major Conurbation". LSOAs in the remaining urban categories in this classification are deemed "suburban". In our final analysis, we consider data for the 3,226 urban LSOAs, 6,432 suburban LSOAs and 4,570 rural LSOAs for which we have scenicness and happiness data.

LSOA-level income data

As a metric of the economic environment an individual may be passing through at a given point in time, we consider the median household income of each LSOA, determined using Experian Demographic Data (Experian, 2011).

Land cover data

To determine whether the environments that individuals experience are natural or built-up, we use data on land cover from the 25m-resolution UK Land Cover Map 2007 (LCM) (Morton et al., 2014). Table 5.2 lists which land cover types have been deemed to be natural versus built-up.

Table 5.2. Land cover data.
This table shows which land cover types from the 25m-resolution UK Land Cover Map 2007 (LCM) (Morton et al., 2014) have been deemed to be natural, and which have been deemed to be built-up.

LCM2007 class	Habitat
Broadleaved woodland	Natural
Coniferous woodland	
Arable and Horticulture	
Improved Grassland	
Rough Grassland	
Neutral Grassland	
Calcareous Grassland	
Acid Grassland	
Fen, Marsh and Swamp	
Heather	
Heather grassland	
Bog	
Montane habitats	
Inland Rock	
Salt water	
Freshwater	
Supra-littoral Rock	
Supra-littoral Sediment	
Littoral Rock	
Littoral Sediment	
Saltmarsh	
Urban (including Bare and Urban)	Built-up
Suburban (including Urban industrial and Urban suburban)	

5.3 Results

Table 5.3 presents the results of our analysis. Visual inspection of this table reveals that the directions of the relationships between many of the control variables and happiness are in line with what we might intuitively expect, and accord with previous research. For example, commuting is negatively associated with happiness (Stutzer & Frey, 2008) while leisure activities such as resting, gardening (Ferrer-i-Carbonell & Gowdy, 2007), walking (Richards et al., 2015) and spending time with family and friends (Lelkes, 2006) are positively associated with happiness. Rain is associated with reduced happiness, while higher temperatures and more hours of sunshine per day are associated with increased happiness (Rehdanz & Maddison, 2005). Crucially however, we find that people do report themselves to be happier when in a more scenic location (β = 3.527, CI = [2.551, 4.504], N = 138407, p < 0.001), even after controlling for weather, activities, companionship, weekdays or weekends, and previous usage of the *Mappiness* app.

Table 5.3. Is happiness greater in more scenic locations? Estimated model parameters for fixed effects model.
The dependent variable is Happiness, scaled to 0-100. Note that while all the activities that people report on in the *Mappiness* app have been included in the model (Tab. 5.1), we only report the activities that we expect to be common in scenic environments. We find that people are happier when in more scenic locations, even after accounting for environmental factors such as presence of green space, or whether the location is a built-up area or a natural habitat.

	Model 1: scenicness only		Model 2: scenicness + environmental variables	
	Coeff.	*95% C.I.*	*Coeff.*	*95% C.I.*
Environment variables				
Scenicness	3.527***	[2.551, 4.504]	2.770***	[1.757, 3.783]
Natural habitat	–		0.574***	[0.303, 0.844]
Percentage of green space	–		-0.451	[-0.999, 0.0979]
Area-level median household income	–		-0.255	[-0.654, 0.144]
Urban	–		-0.282	[-0.668, 0.103]
Rural	–		0.608***	[0.263, 0.954]
Suburban (base category)	–		–	
Participant is...				
Home	0.375	[-0.113, 0.862]	0.442	[-0.0452, 0.930]
Work	-3.252***	[-3.764, -2.739]	-3.217***	[-3.730, -2.705]
Elsewhere (base category)	–		–	
Companionship				
Spouse, partner, girl/boyfriend	4.215***	[3.858, 4.572]	4.144***	[3.787,4.501]
Children	0.564*	[0.0622, 1.066]	0.556*	[0.0543,1.058]
Other family members	1.278***	[0.897, 1.659]	1.196***	[0.812,1.580]
Colleagues, classmates	0.0327	[-0.804, 0.869]	0.00123	[-0.833,0.835]
Clients, customers	2.593***	[1.311, 3.876]	2.566***	[1.280,3.853]
Friends	4.500***	[4.155, 4.846]	4.441***	[4.092,4.790]
Other people participant knows	-1.486***	[-2.147, -0.826]	-1.531***	[-2.192,-0.869]

Selected Activities				
Travelling, commuting	-2.216***	[-2.517, -1.914]	-2.214***	[-2.517, -1.911]
Sleeping, resting, relaxing	1.204***	[0.563, 1.845]	1.133***	[0.494, 1.773]
Talking, chatting, socialising	4.202***	[3.853, 4.552]	4.193***	[3.844, 4.542]
Eating, snacking	1.413***	[1.009, 1.816]	1.426***	[1.022, 1.829]
Walking, hiking	3.918***	[3.513, 4.324]	3.857***	[3.453, 4.261]
Sports, running, exercise	7.221***	[6.530, 7.913]	7.186***	[6.495, 7.878]
Gardening, allotment	3.955***	[3.103, 4.807]	3.958***	[3.105, 4.811]
Birdwatching, nature watching	4.143***	[3.233, 5.053]	3.979***	[3.064, 4.893]
Hunting, fishing	4.994***	[2.275, 7.713]	4.755***	[2.051, 7.460]
+ 33 further activity dummies	Yes		Yes	
Weather				
Wind speed	-0.0326**	[-0.0551, -0.0101]	-0.0332**	[-0.0557, -0.0107]
Cloud cover	-0.0845***	[-0.129, -0.0398]	-0.0879***	[-0.133, -0.0431]
Visibility	0.0000297	[-0.0000559, 0.000115]	0.0000248	[-0.0000608, 0.000110]
Temperature	0.0822***	[0.0561, 0.108]	0.0832***	[0.0571, 0.109]
Hours of daily sunshine	1.149***	[0.772, 1.525]	1.124***	[0.748, 1.501]
Rain	-0.553***	[-0.834, -0.272]	-0.553***	[-0.835, -0.272]
Hours of weekday/weekend and bank holiday dummies (3-hour blocks)	Yes		Yes	
Mappiness usage dummies (participant's response, 1, 2-11, 12-51)	Yes		Yes	
Observations	138,407		138,407	
Groups (participants)	15,444		15,444	
Groups (LSOAs)	14,228		14,228	
R^2	11.6%		11.6%	

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

Comparing scenic environments to natural, green and rural environments

However, this analysis alone is not enough to allow us to determine whether the aesthetics of an environment play a role in happiness that goes beyond the role of nature that previous studies have considered. Indeed, intuitively, we may understand scenic environments to be akin to natural environments or green spaces. Similarly, it seems reasonable to suggest that the most scenic areas of the country may be rural areas rather than urban areas. We explore to what extent scenicness differs from these environmental factors.

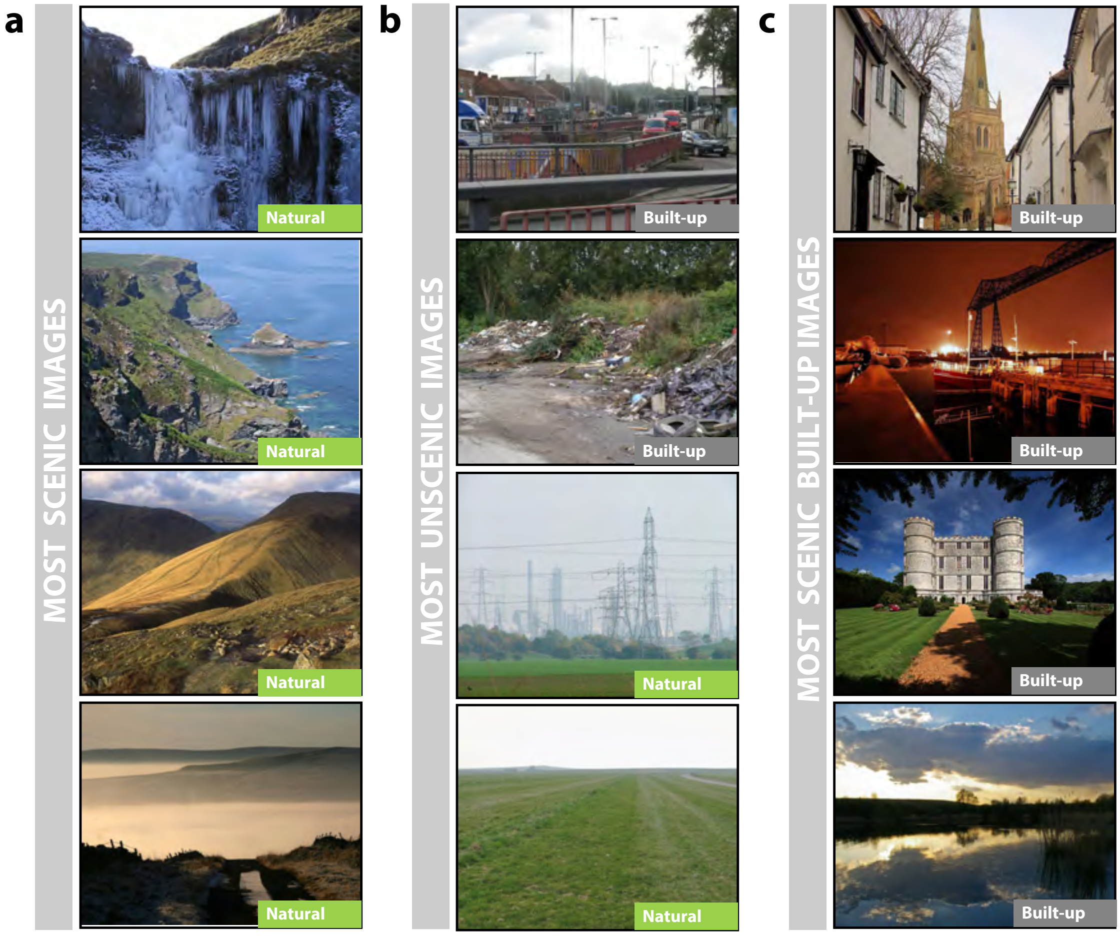


Figure 5.3. Scenic and unscenic images from *Scenic-Or-Not*.
(a) The four most scenic images in England. Visual inspection suggests that scenic images are primarily composed of natural landscapes. They not only contain large areas of green space, but also mountainous landscapes and water features. (b) A sample of the most unscenic images. Such images tend to be taken in built-up areas and might include dense road networks or abandoned rubbish. However, natural areas can also be rated as highly unscenic if industrial structures obstruct the naturally scenic view or if they appear to be largely featureless or desolate. (c) A sample of the top 5% of scenic images in built-up locations. Scenic images in built-up locations can include a variety of features such as quaint villages, structures such as bridges, castle-like structures, and park lakes. Photographers of scenic images from top to bottom: © Copyright Richard Swales, © Copyright Tony Atkin, © Copyright Tom Richardson, © Copyright Helen Wilkinson; Photographers of unscenic images from top to bottom: © Copyright Peter Whatley, © Copyright David Long, © Copyright Mick Garratt, © Copyright Doug Lee; Photographers of scenic built-up images from top to bottom: © Copyright Bob Jones, © Copyright Phil D Mike Searle, © Copyright Glyn Baker. Copyright of the images is retained by the photographers. Images are licensed for reuse under the Creative Commons Attribution-Share Alike 2.0 Generic License. To view a copy of this licence, visit http://creativecommons.org/licenses/by-sa/2.0/.

In order to determine how scenicness ratings compare to classifications of environments as natural or built-up, we use land cover data (Morton et al., 2014) to categorise the geo-located coordinates of each image for which we have a scenic rating as either a natural environment or a built-up environment. We find that the scenic ratings in natural environments (M = 4.16, Mdn = 4.14) do tend to be higher than the scenic ratings in built-up environments (M = 2.86, Mdn = 2.60; W = 326330000, N = 119377, p < 0.001, Wilcoxon rank sum test with continuity correction). Similarly, using data from the *2011 Rural-Urban Classification* (Office for National Statistics, 2013), we find that scenicness is greater in rural environments (M = 4.19, Mdn = 4.14) than in urban and suburban environments combined (M = 3.33, Mdn = 3,20; W = 703750000, N = 119377, p < 0.001, Wilcoxon rank sum test with continuity correction). However, as Figure 5.3 illustrates, images with low scenic ratings are not always taken in built-up environments, such that the distributions of scenic ratings in natural and in built-up environments do overlap (Fig. 5.4).

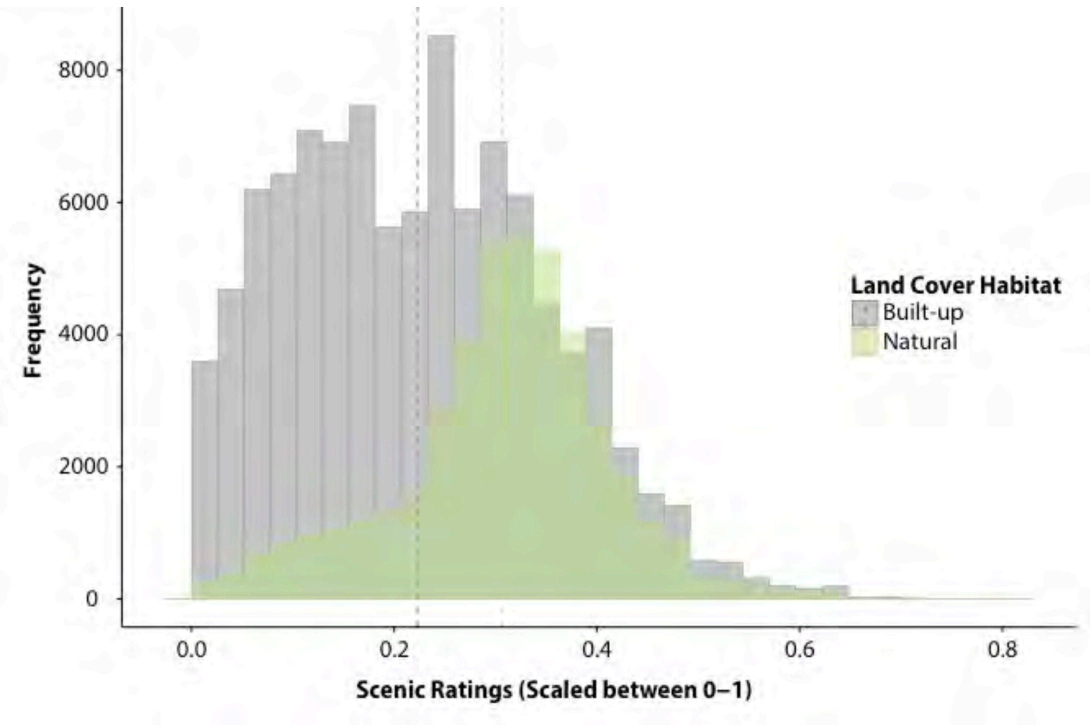


Figure 5.4. Scenicness in built-up versus natural locations.
Scenic ratings tend to be higher in natural environments (marked green) than in built-up environments (marked grey). However, the distributions of ratings exhibit considerable overlap.

We next compare scenicness to green space using data on the percentage of green land cover per LSOA (Department for Communities and Local Government, 2007), in line with a previous analysis of *Scenic-Or-Not* data and relationships to green space (Seresinhe, Preis & Moat, 2015). We find that scenicness is correlated with the percentage of green space, although the effect size is not very high (r_T (119375) = 0.20, p < 0.001, Kendall's rank correlation).

To summarise, scenic ratings are not entirely determined by whether an image was taken in a natural, built-up, urban, suburban or rural environment, and are not equivalent to measurements of green space (Fig. 5.5)

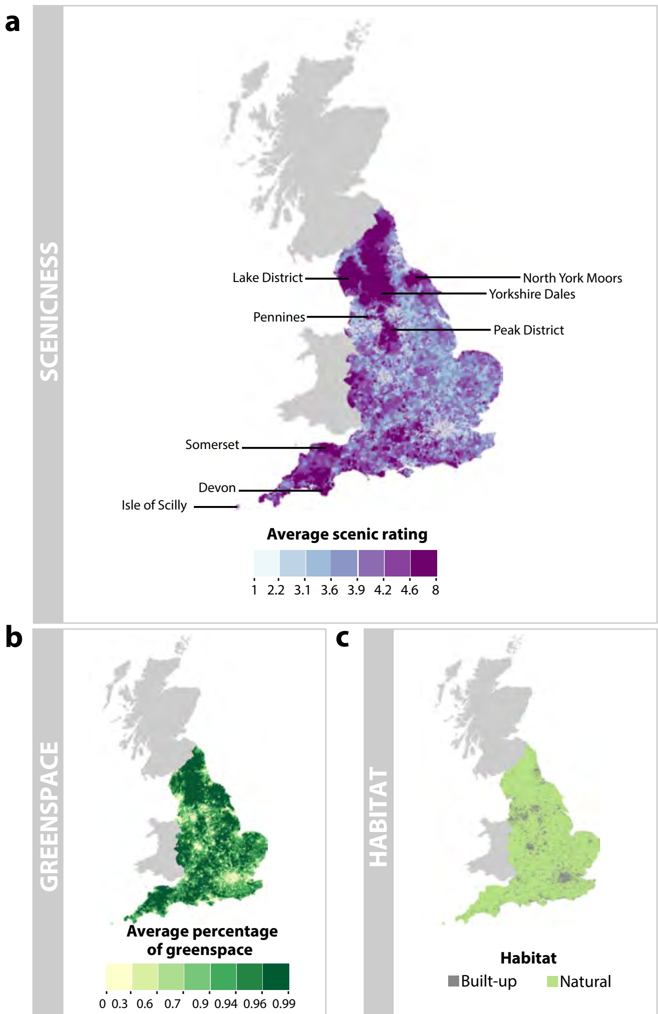


Figure 5.5. Are scenic environments simply green or natural environments?
We explore whether scenic environments are simply natural environments or areas with abundant green space. (a) We calculate the mean scenic rating of all *Scenic-Or-Not* photographs taken for each LSOA and depict these ratings using quantile breaks. Popular notions of scenic areas such as the Lake District and the Peak District are clearly visible on the map. (b) In order to understand whether scenic environments are simply green or natural environments, we consider data on the percentage of green land cover per LSOA (Department for Communities and Local Government, 2007), depicted here using quantile breaks. (c) We also consider data on land cover types (Morton et al., 2014), which we use to classify locations as natural or built-up environments. We find that scenic ratings are not equivalent to measurements of green space and are not entirely determined by whether an image was taken in a natural or built-up environment (see main text for analysis).

We investigate whether a relationship between scenicness and happiness is still found once these more traditional environmental measurements are included in the model. We determine the individual's location at the time of polling, and consider whether the individual is located in a natural or built-up setting, an urban, suburban or rural environment, and what the percentage of green land cover is in the surrounding LSOA. As an additional check, we also include the median household income per LSOA (Experian, 2011) as a control variable, as scenic areas may also be the areas in England in which inhabitants have higher incomes.

Again, Table 5.3 presents the results of our analysis. While our study accords with the hypotheses that people are happier in natural habitats ($\beta = 0.574$, CI = [0.303, 0.844], $N = 138407$, $p < 0.001$) and in rural locations ($\beta = 0.608$, CI = [0.263, 0.954], $N = 138407$, $p < 0.001$), we still find that participants report themselves to be happier when in more scenic areas ($\beta = 2.770$, C.I. = [1.757, 3.783], $N = 138,407$, $p < 0.001$), even after controlling for this wide range of other characteristics of the local environment (Fig. 5.5). Interestingly, our analysis does not provide strong evidence of an effect of green space on happiness ($\beta = -0.451$, CI = [-0.999, 0.0979], $N = 138407$, $p = 0.107$), potentially because the variance in subjective wellbeing attributed to green space in previous studies has been captured by measures of whether the surrounding habitat is natural, rural or indeed scenic.

In these analyses, *Scenic-Or-Not* ratings have been rescaled from the original 1 (not scenic) to 10 (very scenic) scale rating to a 0 - 1 scale. Thus, an increase of 1 additional unit of scenicness in our analysis translates to an increase of 9 in the *Scenic-Or-Not* rating of a neighbourhood. On this basis, the predicted increase in happiness for each increase of 1 in the *Scenic-Or-Not* rating is 0.308 on the 0–100 happiness scale. The predicted increase in happiness of someone moving from a neighbourhood with the lowest scenicness rating of 1 to a neighbourhood with a scenicness rating in the top 10% quartile (i.e., a scenicness rating above 4.67), would therefore be 1.130 points on the 0–100 happiness scale. This is slightly below the increase in happiness observed when participants are sleeping, resting or relaxing (1.133), and greater than the increase in happiness observed when moving from a built-up environment to a natural environment (0.574) or when moving from a suburban environment to a rural environment (0.608). In the same fashion, the predicted increase in happiness of someone moving from a neighbourhood with the lowest possible scenicness rating of 1 to a neighbourhood with the highest possible scenicness rating of 10 would be 2.770 points on the 0–100 happiness scale. This effect is similar in size to the increase in happiness observed when participants are listening to music (2.336) and the decrease in happiness observed when participants are commuting (-2.214) (Fig. 5.6).

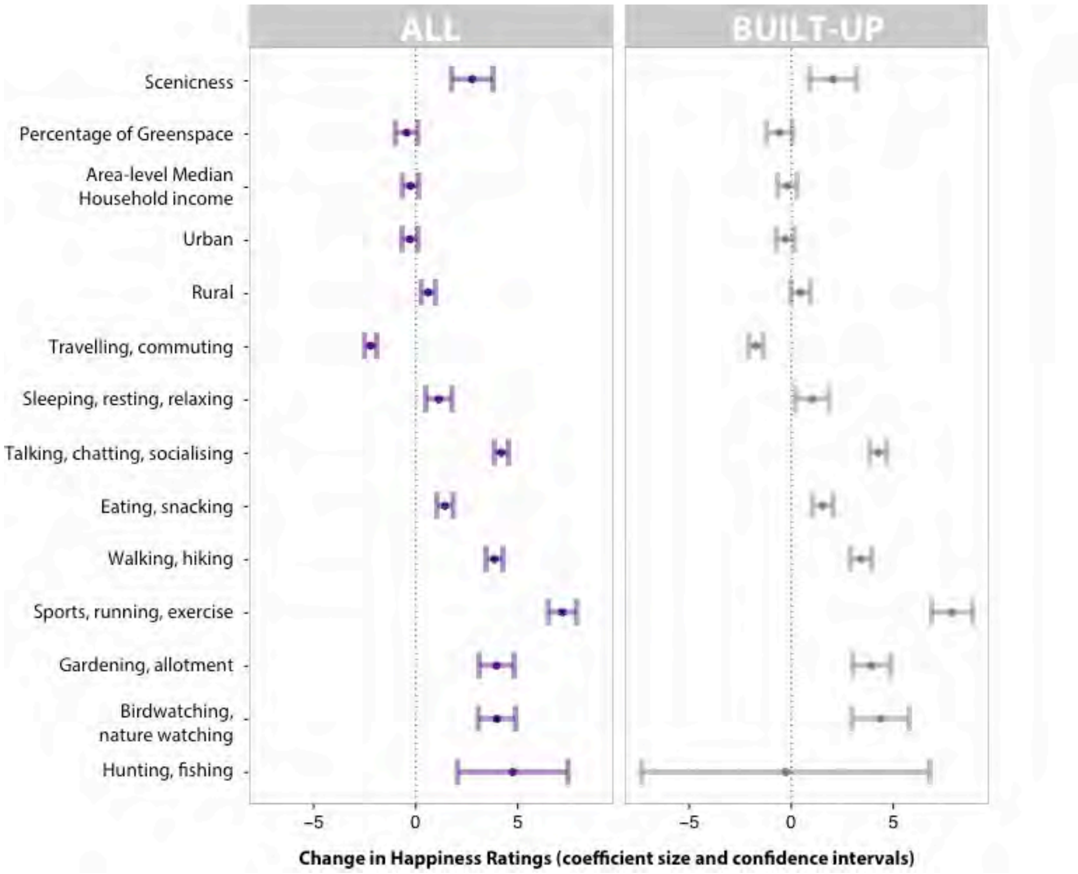


Figure 5.6. Happiness is greater in scenic settings.
Coefficients of selected predictor variables based on results of a fixed effects model. The dependent variable is Happiness, scaled to 0-100, and the coefficient size reflects the change in happiness rating associated with a change of one unit in the given predictor variable. As urban planners and policymakers have the ability to influence the aesthetics of built-up settings, we investigate the effect of scenicness on people's happiness when individuals are located in a built-up rather than a natural location. We find that even within built-up areas, people are still happier when the area is more scenic (right hand panel).

Finally, in order to explore whether data on scenicness can improve our understanding of environmental influences on happiness, given the explanatory power already offered by traditional environmental measurements, we compare three models. All three models contain the contextual control variables, such as weather, companionship and activities. The first model includes only data on scenicness. The second model includes data on scenicness as well as the more traditional measurements of the local environment: whether *Mappiness* users were in a natural habitat, urban, suburban or rural environments; data on green space; and area-level median household income. The third model includes these traditional measurements yet excludes scenicness. In order to compare the fit of the models to each other, we calculate Akaike weights (AICw) following the method proposed by Wagenmakers and Farrell (2004). These weights can be interpreted as the probability of each model, given the data. Table 5.4 illustrates that there is very little evidence for the model that omits the data on scenicness. Instead, we find the strongest evidence for the model that includes data on scenicness plus traditional measurements of the characteristics of the environment.

Table 5.4. Comparing models of the influences of location characteristics on happiness ratings.
To determine which model provides the best fit for predicting happiness, we calculate Akaike weights (AICw), which can be interpreted as probability of each model given the data (Wagenmakers & Farrell, 2004). We find very little evidence for the model that does not include the data on scenicness. Instead, we find the strongest evidence for the model that includes both the traditional environmental measurements and the crowdsourced measurements of scenicness.

Models	**AIC**	**AICd**	**AICw**
With Scenicness only	1144476	51.8	< 0.001
With Scenicness and Traditional Environmental Measurements	1144424	0	> 0.999
With Traditional Environmental Measurements Only	1144465	40.8	< 0.001

Scenic environments or taking a break

One further concern that could be raised about in-situ analyses of the relationship between characteristics of the environment and subjective wellbeing is that people may visit scenic or natural areas when they have the opportunity to take a break from their everyday routine. The *Mappiness* activity questions do allow us to measure whether individuals are undertaking activities that might be associated with holidays, such as sleeping, resting and relaxing, and we include these measurements in our fixed effects analysis. However, in order to verify that the holiday effect is not confounding our analysis, we check whether the relationship between scenic environments and greater happiness still holds for individuals on weekends and bank holidays and when they are not at home or at work, when it could be argued that people might be more likely to be at leisure or taking a break from their daily routine. We find that the link between scenic areas and greater happiness is still robust (β = 4.261, C.I. = [2.550, 5.972], N = 35967, p < 0.001).

Scenic environments and built-up settings

While there is limited scope to improve the beauty of natural settings, urban planners and policymakers do have the ability to influence the aesthetics of built-up areas (Reynolds, 2015). We therefore split our dataset into data for built-up locations versus natural locations, and investigate whether the relationship between scenicness and happiness holds in both. Although the effect size is larger in natural settings, we find that within built-up locations too, people report themselves to be happier when in more scenic locations (natural: $\beta = 5.756$, C.I. = [3.249, 8.262], $N = 37807$, $p < 0.001$; built-up: $\beta = 2.045$, C.I. = [0.890, 3.200], $N = 95113$, $p < 0.001$; Fig. 5.6).

5.4 Discussion

Do individuals encountering more scenic environments during their everyday life experience greater levels of happiness? Here, we have presented what we believe to be the first study able to offer an answer to this question, through national-scale measurements of the aesthetics of different environments and changes in happiness as thousands of individuals experience these various environments during their everyday life. We find that people are indeed happier in more scenic environments, even after controlling for a range of variables such as potential effects of the weather and the activity an individual is engaged in at the time. Crucially, we find that the effect of environmental aesthetics goes beyond the effect of whether an individual is in a natural, green or rural environment, and that even in built-up environments, people are still happier when the area they are in is more scenic.

This distinction between aesthetic appeal and the presence of nature is vital if such research is to be used to inform policy decisions about the design and modification of built and natural environments. Our findings provide evidence that for built environments to be as conducive as possible to the wellbeing of their users, consideration should be given not only to whether areas of nature or green space have been included in the design, but to whether these natural areas are attractive – for which appropriate maintenance may well be required – and indeed to whether the buildings themselves are appealing to the eye. Similarly, our results provide reason to believe that if policymakers allow natural environments to be blighted by unsightly features, these environments will no longer provide the same wellbeing benefits to those who visit them.

Our results also have consequences for theories regarding the impact of our surroundings on our subjective wellbeing. The analysis we report suggests that positive emotions we experience in attractive environments may not only be driven by the presence of nature, in contrast to the central tenet of the biophilia hypothesis (Kellert & Wilson, 1995). How might scenic settings otherwise make us feel happier? According to Attention Restoration Theory (Kaplan, 1995), scenes requiring less demand on our attention allow us to become less fatigued, more able to concentrate, and thus perhaps even less irritable. Such restorative settings have often been associated with nature, and in contrast, one can imagine that a bustling urban setting such as Times Square in New York City might demand our full attention. However, more picturesque streets with broad views and fewer distractions might also function as restorative settings. Settings that are more beautiful may also hold our interest for longer, thereby blocking negative thoughts (Ulrich, 1979). Furthermore, certain features of environments commonly associated with scenic environments, such as open spaces and spaces full of light, might make us feel happier simply because we feel safer (Herzog & Chernick, 2000; Loewen, Steel & Suedfeld, 1993). This accords with prospect-refuge theory (Appleton, 1975) as in such spaces one can easily observe “prospects” and avoid possible dangers. We do not rule out the possibility that characteristics of environments we consider scenic remind us of environmental characteristics that we have found beneficial at some point in our evolutionary history. The connection we find between environmental aesthetics and subjective wellbeing may therefore still be due to evolutionary processes, as suggested by the biophilia hypothesis, but not simply due to a preference for a connection with nature, in contrast to biophilia theory (Kellert & Wilson, 1995).

Our analysis does come with the limitation that *Mappiness* users are all Apple iOS users. As Apple products are known for their design appeal, it might be that *Mappiness* participants are more likely to be affected by the aesthetics of their environment. A further concern might be that our scenicness ratings rely on individual photographs, which might not be wholly representative of the aesthetics of the local area. Ratings of photographs might also be influenced by image composition or the weather depicted in the image. However, despite these likely sources of noise, our analyses show that crowdsourced ratings of scenicness do help explain more variance in happiness than traditional environmental measurements alone. Our study takes an important step in providing evidence that the beauty of the environment, and therefore decisions made in the design of environments, might have a crucial impact on people’s everyday happiness.

Chapter 6

Scenicness and evaluative wellbeing: An analysis using annual panel data from *Understanding Society*

6.1 Introduction

In Chapter 5, we explored the connection between one aspect of our wellbeing – experienced everyday happiness – and scenic places. We do indeed find that individuals are happier when visiting more scenic locations, even after controlling for the presence of green space and natural habitats, as well as weather conditions, weekends, leisure activities and the income of local inhabitants. However, if we are to adequately understand the connection between scenic beauty and wellbeing, it is apparent that we will need to consider different aspects of our wellbeing, not only everyday happiness. The connection between beauty and our wellbeing might differ based on precisely what type of wellbeing we are considering. For example, White et al. (2013b) found that individuals report less mental distress when living nearer to the coast, but they did not find a similar association with life satisfaction. (See Chapter 2 for a full discussion on different measures of wellbeing). Some argue that measurements of experienced wellbeing, such as everyday happiness, provide a less distorted picture of an individual's reality, as they are commonly captured through such methods as the Experience Sampling Method (ESM), introduced in Chapter 6, where participants are asked to use a diary to record details of their wellbeing and current situation at prespecified times of the day (Hektner, Schmidt & Csikszentmihalyi, 2007; Shiffman & Stone, 2008). Thus, we do not have to rely on people's recollection of their experiences, which are often susceptible to biases (Hektner, Schmidt & Csikszentmihalyi, 2007; Kahneman et al., 2004). Others argue that studies based on evaluative answers regarding wellbeing, such as "how satisfied are you with your life overall?" might reveal more stable preferences and reflect how people actually make life decisions (Akay, Bargain & Jara, 2017; O'Donnell et al., 2014; Helliwell & Leigh, 2010).

A more in-depth understanding of the connection between wellbeing and scenicness has policy implications. If such a connection is momentary, as can be measured by experienced wellbeing, then we might be better off investing in beautiful places for people to visit to help boost their daily happiness, such as picturesque parks or attractive recreational or social areas at work premises. If we find that such a connection has a lasting impact on people's lives, as can be measured by evaluative wellbeing, then this could justify more substantial investments such as improving the appearance of social housing projects, or beautifying urban infrastructure in the areas in which people live.

In this chapter we explore if the connection between scenicness and wellbeing might hold for measures of evaluative wellbeing. Data from *Understanding Society*, the United Kingdom Household Longitudinal Study (University of Essex (UE), 2017) provides us with rich measurements relating to two key evaluative measures of wellbeing: mental distress, as measured by the General Health Questionnaire (GHQ), and life satisfaction. The survey is carried out on approximately 40,000 households every year, capturing how different aspects of people's lives, including family life, education, employment, finance, health and wellbeing, change over time.

The analyses presented here also have a second key goal. Our study exploring the connection between people's reported health and scenicness (Seresinhe et al., 2015) provided initial evidence between scenic environments and an evaluative measure of physical wellbeing, self-reported health, with measurements obtained from the *2011 Census for England and Wales*. However, in our previous study, we were unable to control for the potential confounding factor that healthy people might self-select to move to locations that are more scenic, as the data we had access to was provided at an aggregate level and related to one point in time alone. *Understanding Society* also provides data on self-reported health, but crucially offers measurements gathered over several years. Also, as the survey collects data on several aspects of people's lives, we are able to control for an even wider range of potential confounding variables. Therefore, in this chapter we also attempt to address the “self-selection” bias in our reported health study (Seresinhe et al., 2015) – i.e., do people who are already physically healthy choose locations that are more scenic?

Our two goals for the analyses reported in this chapter are therefore to find answers to the following two questions: (1) Does living in more scenic areas lead to less mental distress and greater life satisfaction? (2) Do individuals with high wellbeing self-select to move to scenic areas?

6.2 Method

Wellbeing ratings

Data on wellbeing is drawn from the first seven waves of *Understanding Society*, the United Kingdom Household Longitudinal Study, which comprises data collected from 2009 to 2016 (UE, 2017). The survey includes the responses of adult (age 16 and over) members of approximately 40,000 households. Households recruited in the first wave are interviewed each year to capture information on changes to their individual and household circumstances on a wide range of themes such as family life, education, employment, finance, health and wellbeing.

Mental distress is measured using the General Health Questionnaire, a 12-item survey asking respondents how often in the last few weeks they had been able to concentrate, had lost sleep over worry, played a useful role, were capable of making decisions, were constantly under strain, couldn't overcome their difficulties, enjoyed day-to-day activities, were able to face up to problems, were unhappy or depressed, had lost confidence, had been believing they are worthless, and had been reasonably happy. We recode the raw data from the *Understanding Society* survey using the widely-used 0 - 12 coding scheme (e.g. White et al., 2013a), where the first two categories ("not at all" or "no more than usual") are coded as 0 and the last two categories ("rather more than usual" or "much more than usual") are coded as 1. Summed, the GHQ scores therefore range from 0 to 12. We invert the GHQ scores so that higher scores indicate low mental distress.

We extract data on life satisfaction using the global life satisfaction question "How dissatisfied or satisfied are you with your life overall?" from the *Understanding Society* survey. Responses range from 1 ("Completely dissatisfied") to 7 ("Completely satisfied"). We measure self-reported health with the question "In general, would you say your health is…" 1 ("Excellent") to 5 ("Poor").

Scenic ratings

We combine our wellbeing ratings with scenic ratings at the level of LSOA. LSOAs are areas defined by the Office for National Statistics for statistical analyses that have a mean population size of around 1,600 and an area of between 0.018 square km and 684 square km.

The *Understanding Society* survey has household responses covering 27,514 LSOAs. However, we only have scenic ratings from *Scenic-Or-Not* for 11,454 of the 27,514 *Understanding Society* LSOAs, and only 6,932 LSOAs have aggregated ratings from more than four images. Thus, we use our Scenic CNN introduced in Chapter 4 to predict scenic ratings for further LSOAs covered by *Understanding*

Society to expand the coverage in our study, as well as to increase the robustness of our scenic ratings.

We choose to predict scenicness for *Geograph* images (using out Scenic-Or-Not CNN), rather than *Google Street View* images, as we achieve a higher performance score of 0.658 Kendall Rank Correlation for the former (See Chapter 4 for a full description of the different models). In our final analysis, we only include LSOAs that have at least four actual *Scenic-Or-Not* ratings, or that have four images for which we can predict the scenic ratings. This approach allows us to obtain scenic ratings for 21,390 LSOAs (Fig. 6.1).

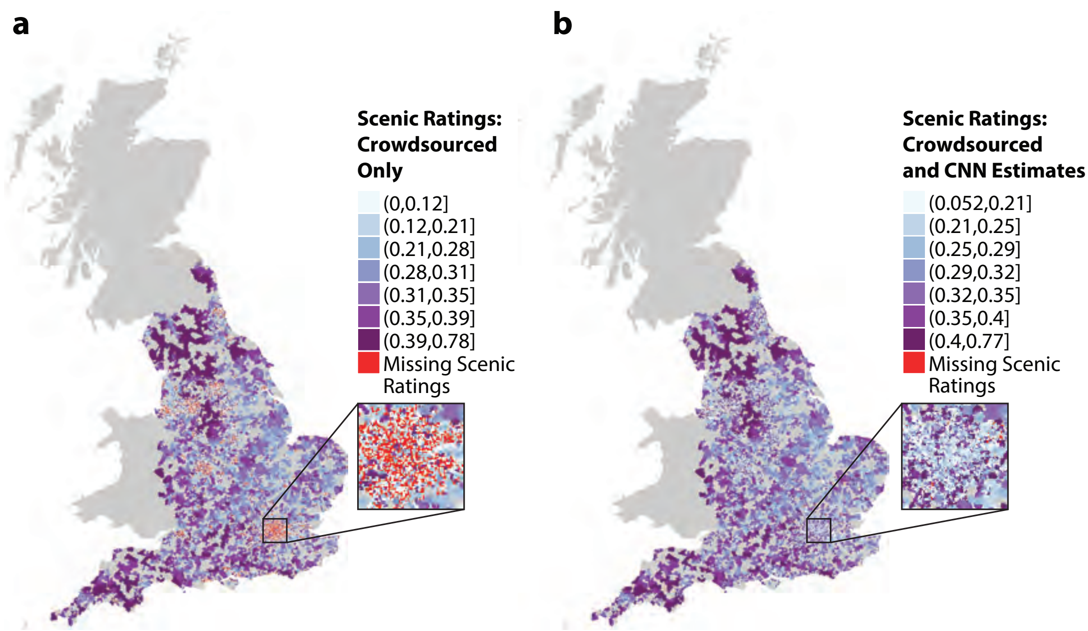


Figure 6.1. Scenic ratings available for LSOAs covered in the *Understanding Society* survey.
Areas marked in red are LSOAs for which we have data from *Understanding Society* but no available Scenic ratings. You can clearly see in (b) that estimating scenic ratings using our Scenic-Or-Not CNN (Chapter 4) allow us to expand the coverage of LSOAs to many more LSOAs for which we have data from *Understanding Society* in comparison to (a). This is particularly helpful in urban areas where LSOAs tend to be smaller in size, and therefore not covered by our original *Scenic-Or-Not* data.

In order to ensure that scenicness ratings are easily comparable to other dummy variables included in our analysis, we rescale both the *Scenic-Or-Not* ratings and Scenic-Or-Not CNN scenic predictions to 0 ("not scenic") to 1 ("extremely scenic") prior to aggregating scenicness measurements on an LSOA basis. After doing this, the range of scenic ratings is 0.052 to 0.77. In other words, no LSOA has a perfect score of 1.

Individual and household level controls

Following similar studies (Houlden, Weich & Jarvis, 2017; White et al 2013a; White, et al., 2013b) that explore the connection between environmental factors, including green space and coastal proximity, and wellbeing, we include the following potential confounding variables in our analysis: age; diploma or degree level qualification; marital status; living with children; household income per capita; activity-limiting health; employment status (employed, self-employed, unemployed, retired, in education, family carer, other); residence type (detached, semi-detached, terraced, flat); household space (less than 1, 1 to 3, more than 3 rooms); homeowner status; and commuting time to work.

Area level controls

We also include LSOA-level environmental variables in our analysis to account for potential area-level confounding factors. We include percentage of green space and water, as obtained from the *Generalised Land Use Database Statistics for England 2005* (Department for Communities and Local Government, 2007). We include whether an LSOA is "urban", "suburban" and "rural", as defined using data from the *2011 Rural-Urban Classification* (Office for National Statistics, 2013). We define "urban" LSOAs to be those in the category "Urban Major Conurbation". LSOAs in the remaining urban categories in this classification are deemed "suburban". We also include deprivation data from the relevant domains of the *2010 English Indices of Deprivation*: Income Deprivation, Employment Deprivation, Education Skills and Training Deprivation, and Crime (Department for Communities and Local Government, 2011). The values of these indices increase in line with the proportion of people who experience deprivation in each domain. We also control for regional effects on the level of Government Office Region, now simply called "Region" by the Office for National Statistics – these regions were established in 1994 to divide England into ten broad areas, such as "North East" and "East Midlands".

Analytical model

A key challenge in our analysis is that a very small percentage of respondents move home, specifically 13%. A majority of the movers are not likely to move home more than once within the time period for which we have data. While a fixed effects analysis allows us to control for unobserved individual variables, in this case, such an analysis would not be able to capture the effect of scenicness on individuals, as changes in scenicness would rarely occur. We therefore use the fixed effects filtered (FEF) approach (Pesaran & Zhou, 2016) to evaluate if individuals report increased wellbeing in more scenic areas. Our basic fixed effects model is as follows:

$$W_{it} = \alpha_i + z_i'\gamma + x_{it}'\beta + \epsilon_{it} \tag{1}$$

where W_{it} is the well-being measure (e.g. mental distress or life satisfaction) at time t where $t = 1,2,\dots,T$, and for individual i where $i = 1,2,\dots,N$; α_i are the unobserved individual specific effects; z_i are the time invariant variables (e.g. scenicness) that can vary across individuals; and x_{it} are variables that additionally change over time (e.g. age).

The FEF approach is a two-step procedure, whereby we first estimate the fixed effects ($\hat{\beta}$) on our time-varying variables (x_{it}) and compute the associated residuals ($\hat{u}_{it}$):

$$\hat{u}_{it} = y_{it} - \hat{\beta}' x_{it} \tag{2}$$

We then compute the time averages of these residuals:

$$\bar{\hat{u}}_i = T^{-1} \sum_{t=1}^{T} \hat{u}_{it} \tag{3}$$

We then use this as our dependent variable in a cross-section ordinary least squares (OLS) where we regress $\bar{\hat{u}}_i$ on z_i with an intercept to compute the FEF estimator of our dependent variable $\hat{\gamma}_{FEF}$:

$$\hat{\gamma}_{FEF} = \left[\sum_{i=1}^{N} (z_i - \bar{z})(z_i - \bar{z})'\right]^{-1} \sum_{i=1}^{N} (z_i - \bar{z})(\bar{\hat{u}}_i - \bar{\hat{u}}), \tag{4}$$

$$\hat{\alpha}_{FEF} = \bar{\hat{u}} - \hat{\gamma}'_{FEF}\bar{z} \tag{5}$$

where

$$\bar{\hat{u}} = N^{-1} \sum_{i=1}^{N} \bar{\hat{u}}_i \tag{6}$$

Table 6.1. Estimates from the fixed effects filtered models.

	Model 1: Less Mental Distress		Model 2: Life Satisfaction		Model 3: Self-reported health	
	Coeff.	*95% C.I.*	*Coeff.*	*95% C.I.*	*Coeff.*	*95% C.I.*
Environment variables						
Scenicness	0.109	[-0.171,0.388]	-0.031	[-0.17,0.109]	0.108*	[0.002,0.214]
Green space (%)	-0.114	[-0.318,0.09]	0.076	[-0.028,0.179]	-0.071	[-0.142,0.001]
Water (%)	0.151	[-0.252,0.554]	0.112	[-0.09,0.315]	0.008	[-0.144,0.159]
Urban	-0.100*	[-0.196,-0.004]	-0.046	[-0.094,0.002]	-0.002	[-0.038,0.035]
Suburban	-0.098**	[-0.17,-0.025]	-0.032	[-0.069,0.005]	-0.028	[-0.056,0.001]
Rural (base cat.)	–		–		–	
Income deprivation	-0.111	[-0.785,0.562]	-0.438*	[-0.776,-0.101]	0.180	[-0.06,0.419]
Employment deprivation	-0.303	[-1.05,0.444]	0.235	[-0.136,0.607]	-0.628***	[-0.903,-0.354]
Education deprivation	-0.241	[-0.525,0.043]	-0.332***	[-0.476,-0.187]	-0.445***	[-0.548,-0.341]
Crime	-0.254	[-0.533,0.025]	-0.314***	[-0.454,-0.174]	-0.087	[-0.192,0.018]
Regions as dummies	Yes		Yes		Yes	
Individual variables						
Age						
16-19 years old	0.117	[-0.169,0.403]	0.214**	[0.073,0.355]	0.135***	[0.055,0.215]
20-29 years old	-0.153	[-0.402,0.096]	0.085	[-0.037,0.208]	0.119***	[0.049,0.188]
30-39 years old	-0.188	[-0.384,0.009]	0.030	[-0.071,0.132]	0.143***	[0.087,0.198]
40-49 years old	-0.157	[-0.321,0.008]	-0.001	[-0.089,0.088]	0.122***	[0.074,0.17]
50-59 years old	-0.077	[-0.209,0.055]	-0.004	[-0.078,0.071]	0.090***	[0.05,0.13]
60-69 years old	0.076	[-0.011,0.163]	0.063*	[0.009,0.117]	0.068***	[0.039,0.097]
70 and older (base category)						
Diploma or degree	-0.035	[-0.099,0.029]	0.083***	[0.052,0.113]	0.014	[-0.004,0.032]
Married	0.012	[-0.174,0.198]	0.076	[-0.017,0.168]	-0.025	[-0.075,0.024]
Divorced or separated	-0.281***	[-0.443,-0.12]	-0.129**	[-0.209,-0.048]	-0.014	[-0.057,0.029]
Living with children	-0.130	[-0.288,0.028]	0.070	[-0.004,0.145]	-0.013	[-0.053,0.026]
Household income[a]	0.066***	[0.037,0.096]	0.028***	[0.014,0.042]	-0.003	[-0.01,0.005]
Activity-limiting health	-0.527***	[-0.574,-0.48]	-0.189***	[-0.213,-0.165]	-0.297***	[-0.311,-0.283]
Employment status						
Employed	0.266	[-0.15,0.681]	0.013	[-0.257,0.282]	0.065	[-0.067,0.197]
Self-employed	0.349	[-0.076,0.775]	0.064	[-0.21,0.338]	0.095	[-0.04,0.229]
Unemployed	-0.812***	[-1.238,-0.386]	-0.292*	[-0.564,-0.02]	-0.050	[-0.184,0.084]
Retired	0.240	[-0.186,0.665]	0.088	[-0.186,0.362]	0.035	[-0.099,0.169]
Education/training	0.038	[-0.383,0.459]	0.121	[-0.145,0.388]	0.032	[-0.102,0.165]
Family carer	-0.023	[-0.452,0.406]	-0.015	[-0.289,0.259]	0.051	[-0.084,0.185]
Other	0.012	[-0.472,0.497]	-0.033	[-0.325,0.26]	0.042	[-0.102,0.185]
Resident type						
Detached	0.215*	[0.006,0.424]	-0.081	[-0.202,0.04]	0.011	[-0.052,0.074]
Semidetached	0.228*	[0.019,0.436]	-0.073	[-0.192,0.047]	0.018	[-0.044,0.08]
Terraced	0.249*	[0.039,0.458]	-0.033	[-0.153,0.088]	0.025	[-0.037,0.088]
Flat	0.238*	[0.013,0.464]	-0.066	[-0.194,0.062]	0.040	[-0.026,0.105]
Other (base cat.)						
Household space						
< 1 rooms/person	0.207*	[0.026,0.388]	0.093*	[0.002,0.184]	0.030	[-0.02,0.08]
1-3 rooms/person	0.116	[-0.009,0.242]	0.027	[-0.034,0.088]	0.016	[-0.017,0.049]
> 3 rooms/person (base category)						
Home owner	0.147	[-0.05,0.344]	0.061	[-0.04,0.162]	-0.012	[-0.069,0.045]

Commuting time						
15 minutes or less	0.174**	[0.069,0.279]	0.028	[-0.022,0.078]	0.046***	[0.019,0.073]
>15-30 minutes	0.128*	[0.02,0.237]	0.005	[-0.047,0.057]	0.029*	[0.001,0.057]
>30-50 minutes	0.105	[-0.004,0.214]	-0.013	[-0.066,0.04]	0.018	[-0.011,0.047]
> 50 minutes (base category)						
Observations	146,604		146,139		151,781	
Groups	42,279		42,171		44,372	

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

6.3 Results

Does living in more scenic areas lead to less mental distress and greater life satisfaction?

Table 6.1 presents the results. We find no evidence that people report better evaluative mental wellbeing (as measured by "mental distress" and "life satisfaction") when they live in a more scenic area (mental distress: β = 0.109, *CI* = [-0.171,0.388], *N* = 146,604, *p* = 0.447; life satisfaction: β =-0.031, *CI* = [-0.17,0.109], *N* = 146,139, *p* = 0.667). This finding contrasts with the results reported in Chapter 5, which indicate that people report greater happiness (or "experienced mental wellbeing") when they *visit* more scenic areas. We reflect on reasons why this may be the case in the discussion section. We do however find that people who live in more scenic areas report better health (β = 0.108*, CI = [0.002,0.214],* *N* = 151,781, *p* = 0.046), in line with previous results (Seresinhe et al., 2015).

Do individuals with high wellbeing self-select to move to scenic areas?

We also address the potential confounding factor in our previous analysis, which is that healthy people may choose to live in more scenic areas. We do not have any direct data on whether or not a person has moved; we are only able to identify the location of a respondent at the level of LSOA. Therefore, we denote an individual as having moved in our analysis if the individual has responded to the *Understanding Society* survey from a different LSOA than in the previous year. Note that this will not capture individuals that moved house within the same LSOA.

We then conduct a logistic regression analysis to predict whether a person will move or not in the following year, as well as an additional logistic regression analysis to predict whether a person will move to a more scenic place in the following year. Table 6.2 highlights that people who report better health in a given year are more likely to move in the next year (*β = -0.0382, CI = [-0.0674,0.00895]*, *N* = 120,789, *p* = *0.010*). However, we do not find evidence that they move to more scenic places (β = -0.030, CI = [-0.0703,0.00983], *N* = 120,789, *p* = 0.139)

Table 6.2. Are healthy people more likely to move the following year?

	Will move		Will move to a more scenic place	
	Coeff.	*95% C.I..*	*Coeff.*	*95% C.I..*
Self-reported health	-0.0382*	[-0.0674,-0.00895]	-0.0302	[-0.0703,0.00983]
Environment variables				
Scenicness	-0.0675	[-0.393,0.258]	-8.037***	[-8.538,-7.536]
Green space (%)	-0.764***	[-0.961,-0.568]	-0.824***	[-1.090,-0.558]
Water (%)	0.367	[-0.0282,0.762]	-0.320	[-0.990,0.350]
Urban	-0.294***	[-0.405,-0.183]	-0.518***	[-0.677,-0.360]
Suburban	-0.0572	[-0.142,0.0272]	-0.220***	[-0.344,-0.0967]
Rural (base category)	–		–	
Income deprivation	-1.947***	[-2.673,-1.222]	-1.249*	[-2.225,-0.272]
Employment deprivation	0.590	[-0.225,1.406]	0.162	[-0.930,1.255]
Education deprivation	-0.282	[-0.591,0.0284]	-0.478*	[-0.900,-0.0563]
Crime	0.445**	[0.131,0.759]	-0.0938	[-0.516,0.328]
Regions as dummies	Yes		Yes	
Individual variables				
Age				
16-19 years old	1.524***	[1.262,1.787]	1.219***	[0.860,1.578]
20-29 years old	2.039***	[1.811,2.266]	1.734***	[1.430,2.039]
30-39 years old	1.583***	[1.362,1.805]	1.435***	[1.139,1.732]
40-49 years old	0.975***	[0.754,1.196]	0.909***	[0.612,1.206]
50-59 years old	0.575***	[0.352,0.797]	0.478**	[0.177,0.780]
60-69 years old	0.558***	[0.384,0.732]	0.602***	[0.363,0.841]
70 and older (base category)				
Diploma or degree	0.0748	[-0.0234,0.173]	0.117	[-0.0149,0.250]
Married	-0.0671	[-0.171,0.0368]	0.00912	[-0.133,0.151]
Divorced or separated	0.261***	[0.167,0.354]	0.160*	[0.0315,0.288]
Living with children	-0.0397	[-0.136,0.0566]	0.00363	[-0.128,0.135]
Household income[a]	0.145***	[0.0973,0.193]	0.175***	[0.108,0.243]
Activity-limiting health	-0.0511	[-0.128,0.0255]	-0.0893	[-0.196,0.0172]
Employment status				
Employed	0.852	[-0.332,2.036]	1.110	[-0.920,3.139]
Self-employed	1.043	[-0.147,2.232]	1.420	[-0.616,3.456]
Unemployed	0.834	[-0.353,2.022]	1.115	[-0.921,3.151]
Retired	0.753	[-0.444,1.951]	0.990	[-1.055,3.034]
In education or training	1.028	[-0.156,2.211]	1.396	[-0.638,3.430]
Family carer	0.757	[-0.432,1.946]	1.079	[-0.957,3.115]
Other	1.116	[-0.111,2.342]	1.647	[-0.424,3.719]
Resident type				
Detached	-0.817***	[-1.034,-0.600]	-0.917***	[-1.208,-0.625]
Semidetached	-0.944***	[-1.155,-0.733]	-1.096***	[-1.377,-0.815]
Terraced	-0.786***	[-0.995,-0.577]	-0.815***	[-1.092,-0.539]
Flat	-0.489***	[-0.699,-0.278]	-0.503***	[-0.781,-0.224]
Other (base category)				
Household space				
< 1 rooms/person	-0.249**	[-0.400,-0.0978]	-0.298**	[-0.502,-0.0927]
1 – 3 rooms/person	-0.214***	[-0.317,-0.111]	-0.299***	[-0.441,-0.158]
> 3 rooms/person (base category)				
Home owner	-1.171***	[-1.240,-1.103]	-1.066***	[-1.163,-0.968]
Commuting time				

15 minutes or less	-0.222***	[-0.336,-0.108]	-0.255**	[-0.411,-0.0986]
>15-30 minutes	-0.134*	[-0.253,-0.0152]	-0.168*	[-0.331,-0.00589]
>30-50 minutes	0.0109	[-0.121,0.142]	0.0609	[-0.117,0.238]
> 50 minutes (base category)				
Observations	120,789		120,789	
Pseudo R^2	0.1150		0.1294	

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

6.4 Discussion

Our previous results provide evidence that people who visit scenic areas experience increased happiness. As the connection between scenicness and wellbeing has different policy implications based on which measure of wellbeing is connected to scenicness, we investigate whether the connection between scenicness and wellbeing also holds for an evaluative measure of wellbeing, mental distress and life-satisfaction. We do not find any evidence that people who live in more scenic places report lower mental distress and higher life satisfaction. However, we do find evidence that people report better health in such places. Might adaptation explain this discrepancy? And why do we still find that scenicness is connected to people's evaluated physical wellbeing?

In 1978, Brickman, Coats and Jannoff-Bulman presented the first convincing empirical evidence in support of the idea of a “hedonic treadmill” (Brickman, Coats & Jannoff-Bulman, 1978). They found that lottery winners, even after initially feeling very good about winning the lottery, over time did not appear to be much happier than a control group. The idea of hedonic adaptation has continued to gain support over the years. For example, Suh, Diener and Fujita (1996) find that for many major life events, only those that occur within the previous three months influence life satisfaction and positive and negative affect.

Our results might indicate that even though individuals experience an initial increase in mental wellbeing when they are first exposed to a more scenic location (as evidenced in our happiness and scenicness study in Chapter 5), this may fade over time, and after some time no longer plays a part in an individual's response when they evaluate their general mental wellbeing. It might also simply be the case that when people answer questions related to their evaluative wellbeing, such as “how satisfied are you with your life?” they may be focusing on central aspects of their life such as their current level of income rather than other general factors that might also be important to them such as a great climate (Schkade & Kahneman, 1994; Kahneman et al., 2006). Therefore, how scenic a person’s local neighbourhood is might not factor into how they answer questions about their evaluative wellbeing. Further studies exploring how mental wellbeing changes over time for those who move to scenic areas would help us understand if adaptation might be the reason why we do not see a connection between scenicness and evaluative measures of wellbeing.

If people are adapting to scenicness, why might we still see a connection between scenic environments and physical wellbeing? Ball et al. (2001) suggest that people might participate in increased physical activity in friendly and attractive surroundings, so this effect could explain our observed result. Exercising outdoors might not be as prone to the adaptation effect, as it could become a feature of people's everyday lifestyle. Thus, when individuals report on their physical wellbeing, this increase in physical activity associated with scenicness may be playing a role in their evaluations. Future research could use the scenic measures developed and explored in this thesis to investigate the connection between physical activity and scenicness on a national scale.

SECTION III
What are scenic places composed of?

We find that people visiting scenic locations report more happiness, and people who live in more scenic locations report better health. Yet, what are these scenic places composed of? Are they simply places abundant in nature? Are all natural areas beautiful? Can buildings be considered beautiful? The following section explores whether we can find answers to these questions that go beyond the simple explanation ‘what is natural is beautiful’.

Chapter 7
Scenic beauty in Great Britain

7.1 Introduction

The beauty of outdoor spaces has long been considered an intangible measure that is difficult to quantify due to its subjective nature. Thus, outdoor beauty is often considered synonymous with nature, as evidenced by the major efforts taken to preserve areas in the countryside (Reynolds, 2015) such as Outstanding Areas of Natural Beauty, and the plethora of paintings depicting natural landscapes presented in museums. But, can we simply assume that all natural areas are beautiful? What environments in towns and cities might also be considered beautiful? In this chapter, we attempt to quantify the composition of scenic beauty for Great Britain.

While individual ideas of beauty are likely to be shaped by our personal cultural and social experiences, there is also reason to believe that our preferences for certain environments are shaped by evolution (Appleton, 1975; Ulrich, 1993; Porteous, 2013). Such preferences may be for natural elements (Orians & Heerwagen, 1992; Kellert & Wilson, 1995), but also for areas with wide vantage points (Appleton, 1996), moderate levels of complexity (Ulrich, 1983; Kaplan, Kaplan & Wendt, 1972; Kaplan & Kaplan, 1989), and enclosedness (Küller, 1972). Thus, it is feasible to suppose that there is a collective sense of beauty that we can measure, and that this may not in fact coincide wholly with only natural beauty.

Traditionally, small-scale surveys have been the most cost-effective method of gathering quantifiable data on what people find beautiful in outdoor spaces. However, such surveys have limited scope in terms of which characteristics of environments they can explore, and have generally only explored a handful of characteristics at a time, such as presence of natural elements (Arthur, 1977; Real et al., 2000; Arriaza et al., 2004), fractal elements (Joye, 2007; Stamps, 2002) or complexity (Ulrich, 1983; Kaplan, Kaplan & Wendt, 1972; Kaplan & Kaplan, 1989).

The ability to crowdsource large amounts of data, coupled with recent advances in computer vision methods, is opening up new avenues for research. Of particular interest are Convolutional Neural Networks (CNNs), a type of neural network model initially popularised by LeCun et al. (1998) that has an efficient network architecture that is well adapted to classifying images and extracting image features. CNNs have been shown to be able to successfully extract information from images, such as object categories (Crowley & Zisserman, 2014; Sharif Razavian et al., 2014), face verification (Taigman et al., 2014) and place categories (Zhou et al., 2014; Zhou et al., 2016).

We use such a CNN, specifically the Places CNN (Zhou et al., 2014; Zhou et al., 2016), to extract hundreds of features from over 200,000 outdoor images from across Great Britain, rated via the online game *Scenic-Or-Not*, in order to develop a deeper and broader understanding of what beautiful outdoor spaces are composed of. We attempt to find answers to our question that go beyond the simple explanation “what is natural is beautiful”. Part of the research reported in this chapter was published in Seresinhe, Preis and Moat (2017).

7.2 Data and methods

Scenic-Or-Not images

We again use data from *Scenic-Or-Not* (as detailed in Chapter 3) to understand what features of outdoor places people find beautiful. *Scenic-Or-Not* presents users with random geotagged photographs of Great Britain, which visitors can rate on an integer scale 1 – 10, where 10 indicates “very scenic” and 1 indicates “not scenic”. The *Scenic-Or-Not* database has over 217,000 images covering 92.5% of the 234,429 land mass 1 km grid squares of Great Britain. To date, over 1.5 million ratings have been submitted.

Extracting scene attributes and place categories from Scenic-Or-Not images

For each *Scenic-Or-Not* image, we use the Places205 AlexNet CNN (Zhou et al., 2014), introduced in Chapter 4, that has been trained on data from the Scene UNderstanding (SUN) attribute database (Patterson et al., 2014) to extract the probabilities of 102 scene attributes such as “trees” and “flowers”. The SUN attribute database contains 102 discriminative outdoor scene attributes, spanning materials to activities (e.g. “wire”,“vegetation”, “shopping”). We extract probabilities for scene attributes from the FC7 layer (the penultimate fully connected layer) of the AlexNet CNN. Table 4.1 lists all the scene attributes used in our analysis.

We use the more recent Places365 CNN (Zhou et al., 2016), introduced in Chapter 4, trained on the Places2 dataset, a repository of 8 million scene photographs, to extract the probabilities of 365 place category classifications such as “mountain”, “lake natural”, “residential neighbourhood” and “train station platform”. We specifically use the Places365 CNN trained using the 152-layer

Residual Network (ResNet152) architecture (He et al., 2016), as this results in the best classification accuracy. Table 4.2 lists all place categories used in our analysis.

Extracting basic characteristics from Scenic-Or-Not images

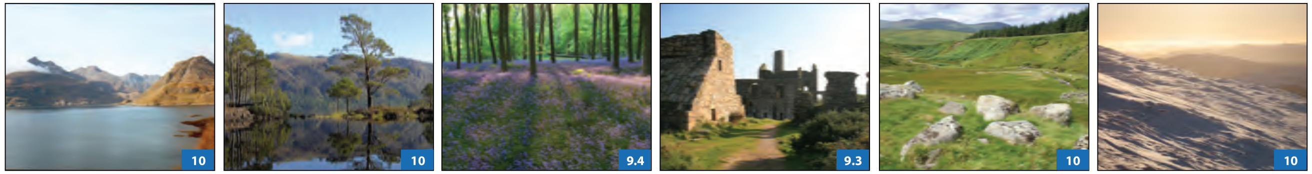
We also explore the basic characteristics of photographs in our scenic ratings dataset, including their colour composition, saturation, brightness and colour variation. We examine each image from *Scenic-Or-Not* on a per-pixel level, with each pixel being allocated to one of eleven colours that constitute the principal colours in the English vocabulary (black, blue, brown, grey, green, orange, pink, purple, red, white, yellow). More details of this procedure and the empirical data that supports it can be found in Chapter 4 (Section 4.2.1).

7.3 Results

Visual inspection of a sample of the most highly scenic images suggests that they conform to widely held notions of beautiful scenery, comprising rugged mountains, bodies of water, abundant greenery and sweeping views (Fig. 7.1a). A sample of the least scenic images suggests that they are often composed of primarily man-made objects such as industrial areas and highways. However, images containing large areas of natural greenery can also be considered unscenic if they look drab, or if man-made objects, such as industrial plants, are obstructing the view (Fig. 7.1b).

a

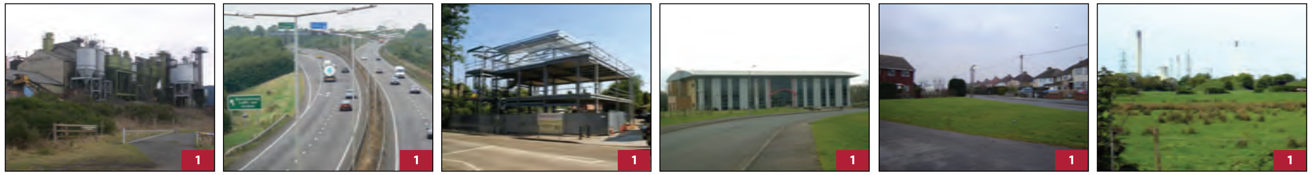
MOST SCENIC IMAGES



Places365 Categories	0.293 Valley 0.203 Lake Natural 0.128 Mountain	0.686 Lake Natural 0.129 River 0.080 Valley	0.857 Forest Broadleaf 0.114 Forest Path 0.018 Field Wild	0.514 Castle 0.152 Ruin 0.047 Kasbah	0.594 Mountain Path 0.337 Tundra 0.026 Valley	0.245 Mountain Snowy 0.203 Ski Slope 0.130 Desert Sand
SUN Scene Attributes	0.856 Natural Light 0.081 Open Area 0.058 Sailing / Boating	0.686 Natural Light 0.129 Still Water 0.080 Natural	0.953 Natural Light 0.046 Nohorizon	0.954 Man Made 0.045 Open Area 0.001 Natural Light	0.997 Natural Light 0.002 Open Area 0.001 Hiking	0.832 Open Area 0.127 Natural Light 0.017 Far Away horizon

b

LEAST SCENIC IMAGES



Places365 Categories	0.947 Industrial Area 0.026 Water Tower 0.011 Construction Site	0.986 Highway 0.003 Raceway 0.003 Forest Road	0.505 Construction Site 0.363 Parking Garage 0.044 Industrial Area	0.279 Industrial Area 0.157 Campus 0.119 Office Building	0.406 Res. Neighborhood 0.187 Industrial Area 0.065 Motel	0.251 Farm 0.175 Field Cultivated 0.112 Vineyard
SUN Scene Attributes	0.565 Man Made 0.405 Open Area 0.021 Natural Light	1.000 Man Made	0.557 Man Made 0.44 Natural Light 0.002 Open Area	1.000 Man Made	0.867 Grass 0.061 Open Area 0.037 Man Made	0.672 Open Area 0.200 Natural Light 0.066 Vegetation

c

MOST SCENIC URBAN BUILT-UP IMAGES

Places365 Categories	0.786 Canal Natural 0.107 Moat Water 0.025 River	0.787 Forest Road 0.064 Driveway 0.040 Forest Path	0.611 Formal Garden 0.093 Topiary Garden 0.056 Oast House	0.948 Cottage 0.033 Oast House 0.016 House	0.987 Viaduct 0.007 Arch 0.003 Aqueduct	0.588 Church Outdoor 0.181 Tower 0.058 Ruin
SUN Scene Attributes	0.982 Natural Light 0.013 Trees 0.003 Open Area	0.999 Trees	0.652 Grass 0.127 Foliage 0.074 Open Area	0.991 Man Made 0.008 Shingles 0.001 Natural Light	0.989 Open Area 0.010 Man Made	0.518 Vertical Components 0.288 Touring 0.107 Natural Light

Figure 7.1 (previous page). Top three place categories and top three scene attributes of sample scenic and unscenic images across Great Britain.
(a) A sample of the top 5% scenic images seems to accord with widespread notions of beautiful scenery – the images are composed of rugged mountains, picturesque lakes, lush forests, abundant greenery, charming ruins and scenes where one can view the distant horizon. **(b)** Unscenic images appear to be mainly composed of man-made features, for example industrial areas, road networks, construction sites and unsightly buildings. However, we also find images composed of large natural areas scoring as unscenic, such as large areas of bland grass, or beautiful fields hindered by unsightly industrial elements in the distance. **(c)** A sample of the top 5% of scenic images in urban built-up areas reveals that some scenic images in urban built-up areas are reminiscent of countryside scenery, including water features and trees. However, the most scenic images in urban built-up areas can also include man-made features such as gardens, bridges or historical architecture. Only those places categories and scene attributes given a probability of 0.001 or higher have been included in the figure. Photographers of scenic images: © Copyright Gordon Hatton, © Copyright jerry sharp, © Copyright Andrew Smith, © Copyright Chris Allen, © Copyright Peter Standing, © Copyright Richard Webb. Photographers of unscenic images: © Copyright Oliver Dixon, © Copyright Mat Fascione, © Copyright Jeff Tomlinson, © Copyright Gordon Brown, © Copyright Graham Clutton, © Copyright Mike Harris. Photographers of scenic urban built-up images: © Copyright David Pinney, © Copyright N Chadwick, © Copyright David Roberts, © Copyright Jonathan Billinger, © Copyright John Salmon, © Copyright Mike Searle. Copyright of the images is retained by the photographers. Images are licensed for reuse under the Creative Commons Attribution-Share Alike 2.0 Generic License. To view a copy of this licence, visit http://creativecommons.org/licenses/by-sa/2.0/.

We also look at a subset of images that are located in urban areas and do not consist primarily of natural land cover that might be associated with beautiful scenery. We differentiate urban areas from rural areas using area classification data from national statistics sources (Office for National Statistics, 2013; Scottish Government, 2012) We use data on land cover from the *25m-resolution UK Land Cover Map 2007 (LCM)* (Morton et al., 2007) to identify images that are located in primarily built-up rather than natural areas. Table 5.2 lists which land cover types have been deemed natural versus built-up.

The sample of images we inspect suggests that the definition of scenicness in urban built-up settings is more varied than in rural areas (Fig. 7.1c). It appears that the most scenic images in urban areas consist not only of images that might be reminiscent of countryside scenery – such as beautiful canals and tree-lined paths – but of images that also contain man-made features such as historical architecture and bridge-like structures.

The number of photographs in our dataset vastly exceeds the number that could be reasonably examined and characterised by a human encoder. In order to exploit the information contained in all of the photographs in our dataset, rather than a small sample, we build an elastic net model that considers the following features we have extracted from the images: colour composition, 102 SUN scene attributes, and those Places365 place categories that are labelled as outdoor categories, of which there are 205. (Note that these 205 outdoor categories from the Places365 CNN differ from the 205 outdoor and indoor categories from the Places205 CNN.) We specifically choose to use an elastic net model as they have been shown to perform well even in situations where there are highly correlated predictors (Zou & Hastie, 2005). Elastic net models are a compromise between ridge regression and LASSO (Least Absolute Shrinkage and Selection Operator), both of which are adaptations of the linear regression model, with a penalty parameter in order to avoid overfitting. We use cross validation to learn the alpha parameter of the elastic net (the mix between ridge and lasso) as well as the lambda parameter (the penalty).

Figures 7.2 and 7.3 present the features that the elastic net model determines lead to higher and lower scenic ratings, both across the dataset as a whole, and within urban built-up settings in particular. The model accords with intuition, whereby natural features are most associated with greater scenicness. These include “Valley”, “Coast” and “Mountain” for the full dataset (Fig. 7.2) and “Canal Natural”, “Pond”, “Gardens” and “Trees” for urban built-up settings (Fig. 7.3). Man-made features such as “Construction Site”, “Industrial Area”, “Hospital”, “Parking Lot” and “Highway” are most associated with lower scenicness in both models. Interestingly however, we also see feature associations that contradict the “what is natural is beautiful” explanation. In both models, man-made elements can also lead to higher scenic ratings, including historical architecture such as “Church”, “Castle”, “Tower” and “Cottage”, as well as bridge-like structures such as “Viaduct” and “Aqueduct”. Large areas of green space such as “Grass” and “Athletic Field” appear to be unscenic in both models. We hypothesise that this might be due to the fact that images composed primarily of flat grass may lack other scenic features such as trees or hills. We also see features that might have been shaped by our evolved preferences coming out in the results. “No Horizon” and “Open Area” are both negatively associated with scenicness in our model containing all images (Fig. 7.2).

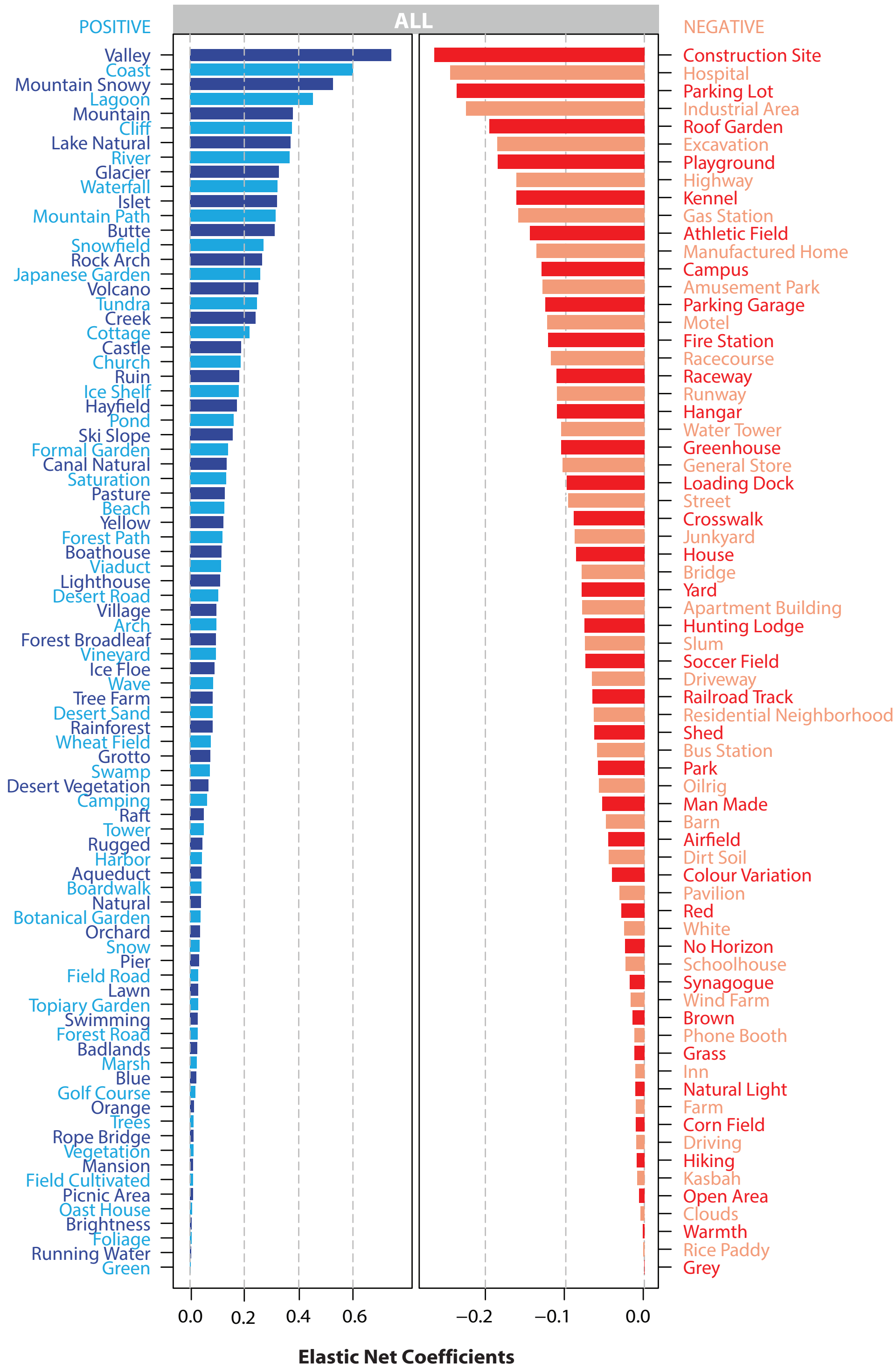


Figure 7.2. Elastic net coefficients for all areas in Great Britain.
We build an elastic net model to identify features that might be most relevant for understanding scenicness. The model that includes all of our *Scenic-Or-Not* images accords with intuition, whereby natural features are most associated with greater scenicness, such as “Valley”, “Coast” and “Mountain”, while man-made features such as “Construction Site” and “Industrial Area” are most associated with lower scenicness. However, man-made features such as “Cottage”, “Castle” and “Lighthouse” are also associated with greater scenicness. In line with Appleton's prospect-refuge theory (1975), we also see features depicted in the results such as “No Horizon” and “Open Areas”, which might reflect preferences shaped by our evolution. We examine this further in the Discussion section. Note that the x-axes for the positive and negative coefficients have different scales.

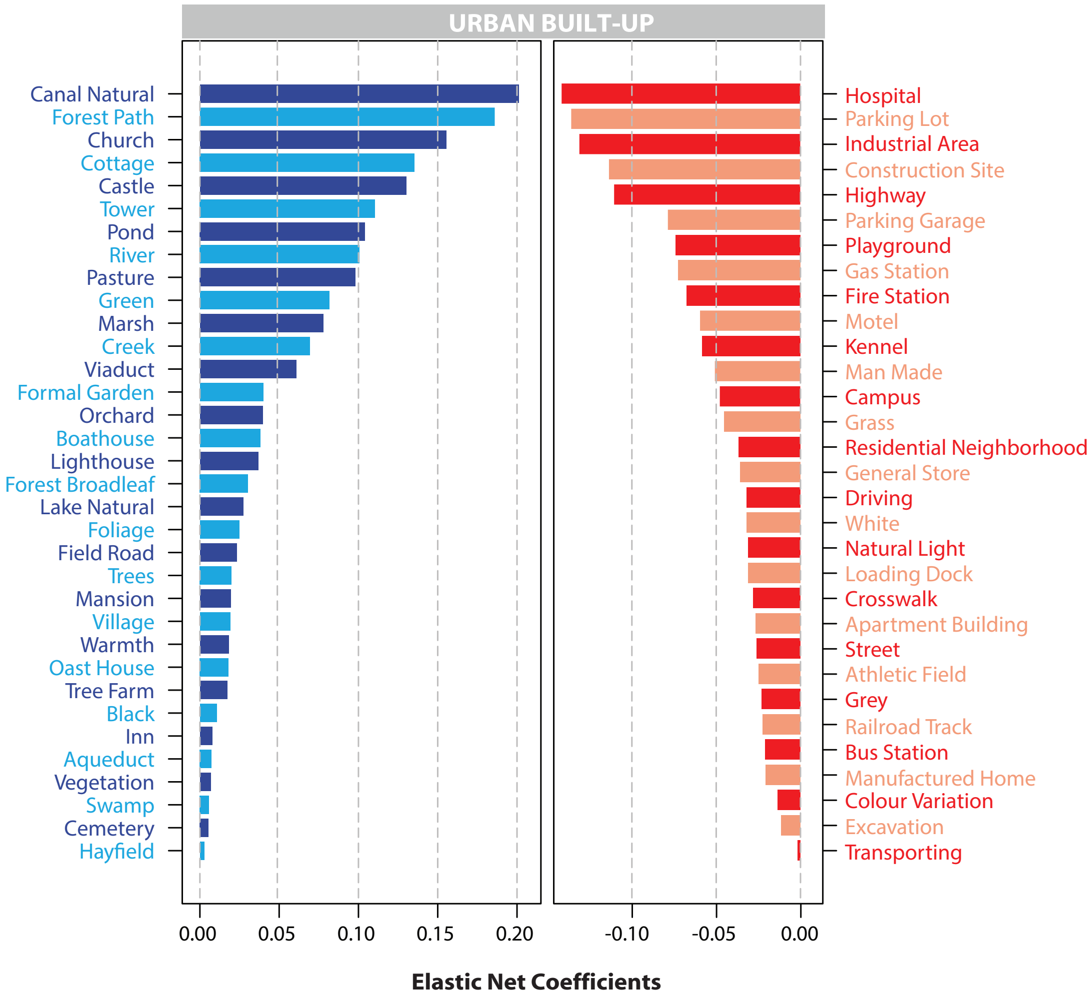


Figure 7.3. Elastic net coefficients for urban built-up areas in Great Britain. We build an elastic net model to identify features that might be most relevant for understanding scenicness in built-up urban areas, which might have their own definition of scenicness. We do indeed find that the definition of scenicness varies for urban built-up locations. We see that natural features that one might more commonly encounter in urban settings such as “Canal Natural”, “Pond” and “Trees” are most associated with greater scenicness. We also see historical buildings such as “Church”, “Castle” and “Tower”, as well as bridge-like structures such as “Aqueduct” are associated with greater scenicness. Interestingly, in both models, large flat areas of green space such as “Grass” and “Athletic Field” are associated with lower scenicness. Note that the x-axes for the positive and negative coefficients have different scales.

Figure 7.4 shows sample images from some of the features mentioned above. Indeed, we can clearly see that large areas of “Grass” might be rated as unscenic as they might lack interesting characteristics such as the contours found in “Valley”. The images with “No Horizon” appear to be those that lack a clear view of the surroundings.

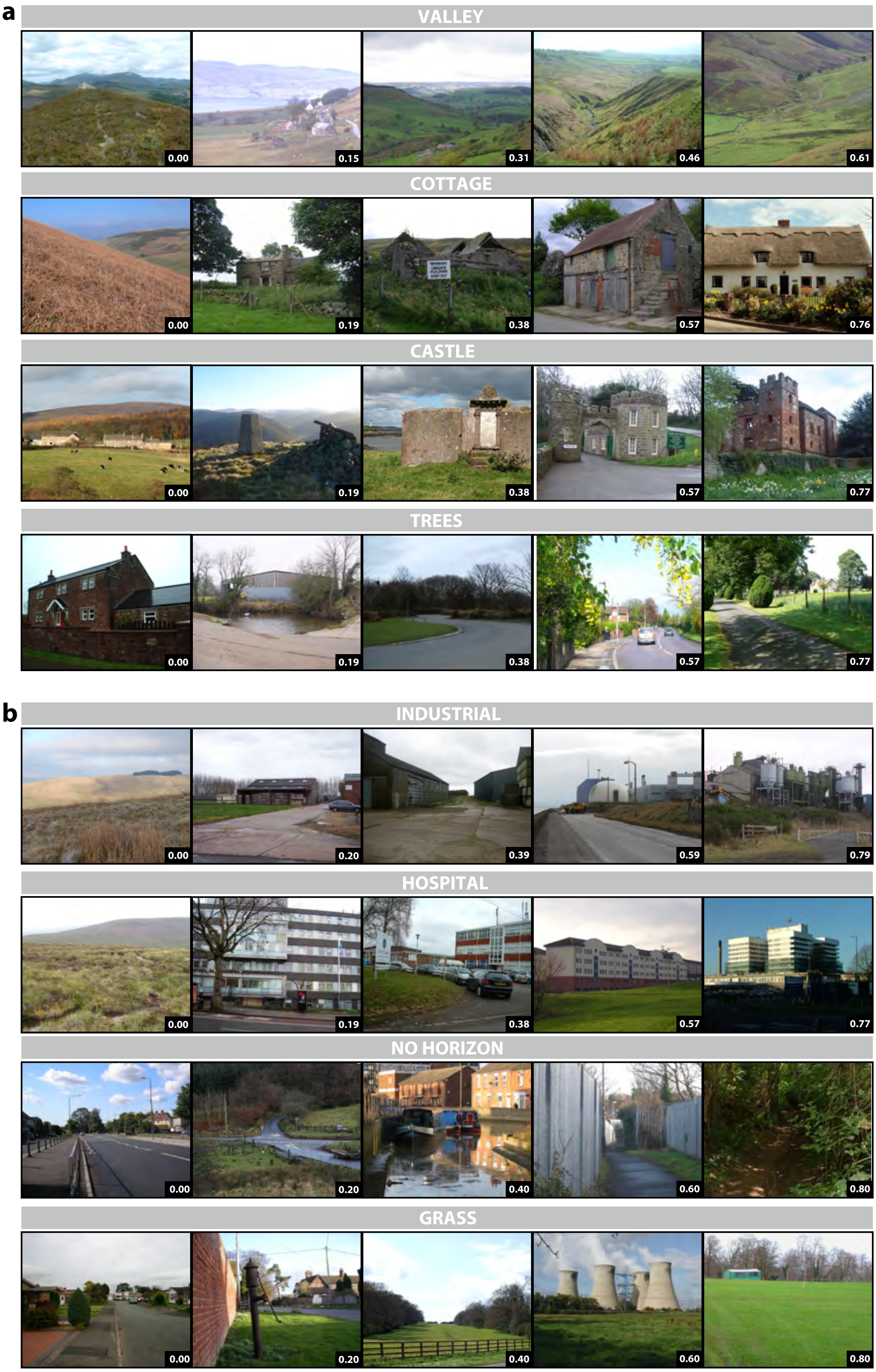

a
VALLEY
0.00
0.15
0.31
0.46
0.61
COTTAGE
0.00
0.19
0.38
0.57
0.76
CASTLE
0.00
0.19
0.38
0.57
0.77
TREES
0.00
0.19
0.38
0.57
0.77
b
INDUSTRIAL
0.00
0.20
0.39
0.59
0.79
HOSPITAL
0.00
0.19
0.38
0.57
0.77
NO HORIZON
0.00
0.20
0.40
0.60
0.80
GRASS
0.00
0.20
0.40
0.60
0.80

Figure 7.4 (previous page). Sample images of features extracted via the Places CNN. For each image, we extract scenic attributes and place categories using the Places CNN (Zhou et al., 2014; Zhou et al., 2016), which assigns a probability score to each attribute. For each attribute, we split the range of probabilities into five equal intervals, and extract a sample image from each interval. **(a)** Sample images with features that are most positively associated with scenicness. Natural features, such as “Valley” and “Trees”, are understandably associated with more scenicness. However, we also find that certain types of man-made structures, such as “Castle” and “Viaduct”, are positively associated with scenicness. **(b)** Sample images with features that are most negatively associated with scenicness. As expected, images that are primarily “Industrial” or contain unsightly man-made objects are not as scenic as those without such features. We also find that if a scene has a restricted field of view, such “No Horizon” images are also rated as unscenic. Surprisingly, we find “Grass” is also negatively associated with scenicness. It might be that images that contain the most grass lack other features such as trees or hill contours, resulting in an uninteresting scene. Photographers of “Valley” images: © Copyright Alan Stewart, © Copyright Anne Burgess, © Copyright Joe Regan, © Copyright Chris Wimbush, © Copyright Chris Eilbeck. Photographers of “Trees” images: © Copyright Alexander P Kapp, © Copyright Bob Jenkins, © Copyright Tom Pennington, © Copyright Colin Smith, © Copyright James Allan. Photographers of “Castle” images: © Copyright Gordon Hatton, © Copyright Iain Macaulay, © Copyright Anne Burgess, © Copyright David Smith, © Copyright Ceri Thomas. Photographers of “Cottage” images: © Copyright Eirian Evans, © Copyright Dennis Thorley, © Copyright jeff collins, © Copyright Colin Grice, © Copyright Robert Edwards. Photographers of “Industrial” images: © Copyright John Lucas, © Copyright Jonathan Billinger, © Copyright Chris Heaton, © Copyright M J Richardson, © Copyright Oliver Dixon. Photographers of “Hospital” images: © Copyright Richard Webb, © Copyright Chris L L, © Copyright Colin Bates, © Copyright Iain Thompson, © Copyright Robin Hall. Photographers of “No Horizon” images: © Copyright Dr Neil Clifton, © Copyright Nigel Brown, © Copyright Kate Nicol, © Copyright Row17, © Copyright Oliver Dixon. Photographers of “Grass” images: © Copyright Stephen Pearce, © Copyright Row17, © Copyright Rob Farrow, © Copyright Paul Glazzard, © Copyright Mike Quinn. Copyright of the images is retained by the photographers. Images are licensed for reuse under the Creative Commons Attribution-Share Alike 2.0 Generic License. To view a copy of this licence, visit http://creativecommons.org/licenses/by-sa/2.0/.

7.4 Discussion

We consider whether crowdsourced data generated from over 200,000 images from the online game *Scenic-Or-Not*, combined with the ability to extract hundreds of features from the images using the convolutional neural network Places365, might help us understand what beautiful outdoor spaces are composed of. We attempt to find answers to this question that go beyond the simple explanation that “what is natural is beautiful”, and explore what features contribute to beauty in urban and built-up settings.

As expected, we find that natural features, such as “Coast” and “Mountain”, are indeed associated with greater scenicness. However, in urban built-up areas the definition of scenicness varies, and instead we see that natural features such as “Pond”, “Garden” and “Trees” are associated with greater scenicness. Surprisingly, we also find that man-made features can also be rated as scenic, in general as well as in urban built-up settings specifically. We find that historical buildings, such as

“Cottage” and “Castle”, as well as bridge-like structures, such as “Viaduct” and “Aqueduct”, are associated with greater scenicness.

What we find to be unscenic might provide the greatest insights. While, as expected, we find that man-made features such as “Construction Site” and “Parking Lots” are associated with lower scenicness, large areas of green space such as “Grass” and “Athletic Field” can also lead to lower scenic ratings. Evolution might have conditioned us to dislike certain natural settings that have attributes that are detrimental to our survival (Ulrich, 1993). For example, we seem to dislike certain natural settings if they appear to be drab or neglected (Akbar, Hale & Headley, 2003), or simply uninteresting to explore (Kaplan, Kaplan & Wendt, 1972; Kaplan & Kaplan 1989). We also find that “No Horizon” and “Open Spaces” are associated with lower scenicness. This accords with Jay Appleton's theory of “prospect and refuge” (Appleton, 1975), which suggests that humans have evolved to prefer outdoor spaces where one can easily survey “prospects” and which contain “refuge” where one can easily hide and avoid potential dangers.

In general, our findings have interesting insights to help inform how we might design spaces to increase human wellbeing. It appears that the old adage “natural is beautiful” seems to be incomplete: flat and uninteresting green spaces are not necessarily beautiful, while characterful buildings and stunning architectural features can be. Particularly in urban areas, features such as ponds and trees seem to be important for city beauty, while spaces that feel closed-off or those that are too open and offer no refuge seem to be spaces that we do not rate as beautiful and do not prefer to spend time in. This accords with research that investigates whether our preferences for certain environments might be shaped by evolution, which explains our attraction not only to natural spaces (Orians & Heerwagen, 1992; Kellert & Wilson, 1995) but also to ones where we might feel more safe (Ulrich, 1993) or spaces that are interesting to explore (Ulrich, 1983; Kaplan, Kaplan & Wendt, 1972; Kaplan & Kaplan, 1989).

Our findings demonstrate that the availability of large crowdsourced datasets, coupled with recent advances in neural networks, can help us develop a deeper understanding of what environments we might find beautiful. Crucially, such advances in technology can help us develop vital evidence necessary for policymakers, urban planners and architects to make decisions about how to design spaces that will most increase the wellbeing of their inhabitants.

Chapter 8
Scenic beauty in Rio de Janeiro

8.1 Introduction

In Chapter 7, we explored hundreds of visual features extracted from over 200,000 images from the online game *Scenic-Or-Not* to develop a deeper understanding what beautiful places are composed of. We find that not only natural features such "Coast", "Mountain" and "Canal Natural" are associated with greater scenicness, but that man-made structures such as "Tower", "Castle" and "Viaduct" can also lead to higher scenic ratings. While, as expected, man-made features such as "Construction Site" and "Parking Lots" are associated with lower scenicness, surprisingly, large areas of flat green space such as "Grass" and "Athletic Field" can also lead to lower scenic ratings. We now explore what might be considered beautiful in a setting remarkably different from Great Britain. If we want to create an algorithm that understands beauty that generalises for the entire world, then it is crucial to understand how the definition of scenicness might vary in different types of cityscapes and landscapes. For our study, we pick the tropical city of Rio de Janeiro in Brazil, a highly urbanised setting amidst lush rainforest and tropical beaches.

8.2 Data and methods

Scenic-Or-Not data for Rio de Janeiro.

We create a similar website to *Scenic-Or-Not, Scenic-Rio* (Fig. 8.1), to gather scenic ratings (between 1 – 10) from images sampled from *Google Street View* for Rio de Janeiro. Creating an even grid of 15,000 latitude and longitude points over the entire city, we then use these points to query the *Google Street View* API for images. Respondents to our exercise were primarily sourced from a massive open online course (MOOC) running on the online learning platform *FutureLearn* from 12 March 2016 to 14 April 2016. In this exercise, MOOC learners were asked to rate at least 20 images, and overall we gathered 57,791 ratings for 4,725 images. We only include images in our analysis that have been rated more than three times and were not reported by our users to be an invalid image (e.g. an image that is no longer being served from Google, or that was taken inside a building).

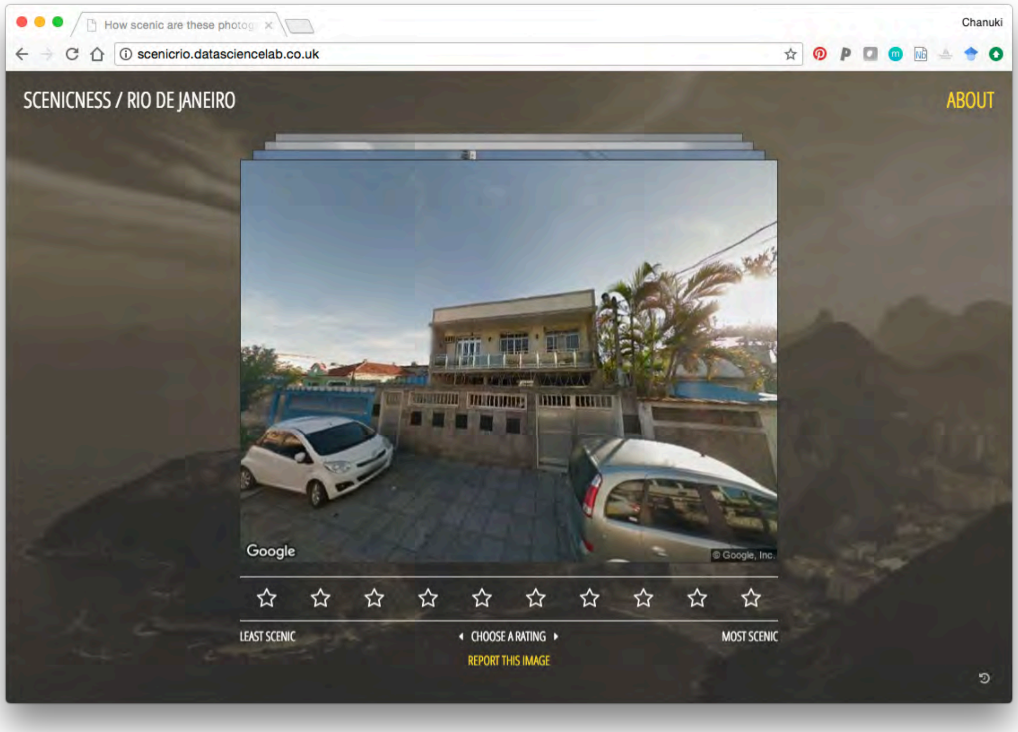


Figure 8.1. ***Scenic Rio*** **voting screen.**
We create a similar website to *Scenic-Or-Not* to gather scenic ratings for Rio de Janeiro. Image @ 2016 Google**.**

Extracting scene attributes, place categories and basic characteristics from Scenic Rio images

Similar to our Great Britain study (Chapter 7), for each *Scenic Rio* image we use the Places205 AlexNet CNN (Zhou et al., 2014) that has been trained on data from the Scene Understanding (SUN) attribute database (Patterson et al., 2014) to extract the probabilities of 102 scene attributes such as “trees” and “flowers”. The SUN attribute database contains 102 discriminative outdoor scene attributes, spanning from materials to activities (e.g. “wire”, “vegetation”, “shopping”). We extract probabilities for scene attributes from the FC7 layer (the penultimate fully connected layer) of the AlexNet CNN. This method is detailed further in Chapter 7.

We use the more recent Places365 CNN trained on the Places2 dataset (a repository of 8 million scene photographs) (Zhou et al., 2018) to extract the probabilities of 365 place category classifications such as “mountain”, “lake natural”, “residential neighbourhood” and “train station platform”. We specifically use the Places365 network, trained using the 152-layer Residual Network (ResNet152) architecture (He et al., 2016), as this results in the best classification accuracy. This method is detailed further in Chapter 7.

Following the same procedure as our scenic images of Great Britain (Chapter 7), we again explore the basic characteristics of photographs in our *Scenic Rio* dataset, including their colour composition, saturation, brightness and colour variation. More details of this procedure and the empirical data that supports it can be found in *Chapter 4 (Section 4.2.1).*

8.3 Results

While the overall visual landscape of tropical Rio de Janeiro is clearly different from that of Great Britain, visual inspection of a sample of the most highly scenic images in Rio de Janeiro indicate similar characteristics of beauty as found in images in Great Britain, including sweeping views of coastal scenery and lush greenery. Of course, we also notice features that are notably different in character from British cities, including tropical foliage, the promenade along the coast as well as contemporary and cliff-side buildings more common to tropical cities (Fig. 8.2a). The sample of least scenic images are also similar in characteristic to images in Great Britain, containing images of manmade objects such as highways and pylons, as well as natural areas that look flat and drab. We also see buildings that appear to be unfinished or in need of some repair, as might be found in some poorer areas in Rio de Janeiro, coming out as being unscenic (Fig. 8.2b).

Following the same process as our Scenicness in Great Britain study (see Chapter 7), we build an elastic net model that considers the following features we have extracted from the images: colour composition, 102 SUN scene attributes, and those Places365 place categories that are labelled as outdoor categories, of which there are 205 (again, note that these 205 outdoor categories from the Places365 CNN differ from the 205 outdoor and indoor categories from the Places205 CNN). We specifically choose to use an elastic net model as they have been shown to perform well even in situations where there are highly correlated predictors (Zou & Hastie, 2005). Elastic net models are a compromise between ridge regression and LASSO (Least Absolute Shrinkage and Selection Operator), both of which are adaptations of the linear regression model, with a penalty parameter in order to avoid overfitting. See Chapter 7 for more details on this method.

a

MOST SCENIC RIO IMAGES

Places365 Categories	0.228 Coast 0.112 Village 0.108 Ocean	0.821 Promenade 0.037 Parking Lot 0.025 Picnic Area	0.800 Balcony Interior 0.090 Roof Garden 0.052 Balcony Exterior	0.881 Field Road 0.031 Forest Road 0.028 Driveway
SUN Scene Attributes	0.583 Open Area 0.402 Far Away Horizon 0.008 Rugged	0.987 Natural Light 0.011 Open Area 0.002 Man Made	0.871 Man Made 0.089 Open Area 0.033 Natural Light	0.862 Natural Light 0.126 Open Area 0.008 Vegetation

b

LEAST SCENIC RIO IMAGES

Places365 Categories	0.370 Slum 0.359 Loading 0.033 Medina	0.432 Industrial Area 0.125 Lock Chamber 0.034 Moat Water	0.172 Volleyball Court 0.114 Excavation 0.103 Construction Site	0.607 Residential Neighb. 0.066 Industrial Area 0.064 Promenade
SUN Scene Attributes	0.992 Man Made 0.006 Natural Light 0.001 Aged	0.995 Man Made 0.004 Clouds 0.001 Natural Light	0.688 Natural Light 0.306 Open Area 0.003 Man Made	0.840 Natural Light 0.118 Open Area 0.030 Driving

Figure 8.2. A sample of the most scenic and least scenic images in Rio.
Visual inspection of a sample of the most scenic images include sweeping views of coastal scenery and lush greenery – features that are also highly rated in Britain. However, we also notice the promenade along the coast as well as architecture that is more common to tropical cities. The sample of least scenic images contains images of manmade objects such as highways and pylons, which we also find unscenic in Great Britain. Less scenic areas in Rio are largely areas with unfinished buildings or areas in need of repair, as might be commonly found in poorer areas in Rio de Janeiro. Images @ 2016 Google**.**

Figure 8.3 presents the features that the elastic net model determines lead to higher and lower scenic ratings in Rio de Janeiro. The coastal "Promenade", a feature well known to be scenic in Rio de Janeiro, is associated with greater scenicness. We also see "Far Away Horizon", as well as rainforest characteristics (picked up as "Green", "Forest Road", "Foliage" and "Forest Broadleaf") in Rio being associated with greater scenicness. Similar to our Great Britain model, man-made features such as "Construction Site", "Industrial Area" and "Parking Lot" are most associated with lower scenicness. Photos that the CNN considers to contain "Slums" also tend to score lower scenic ratings overall.

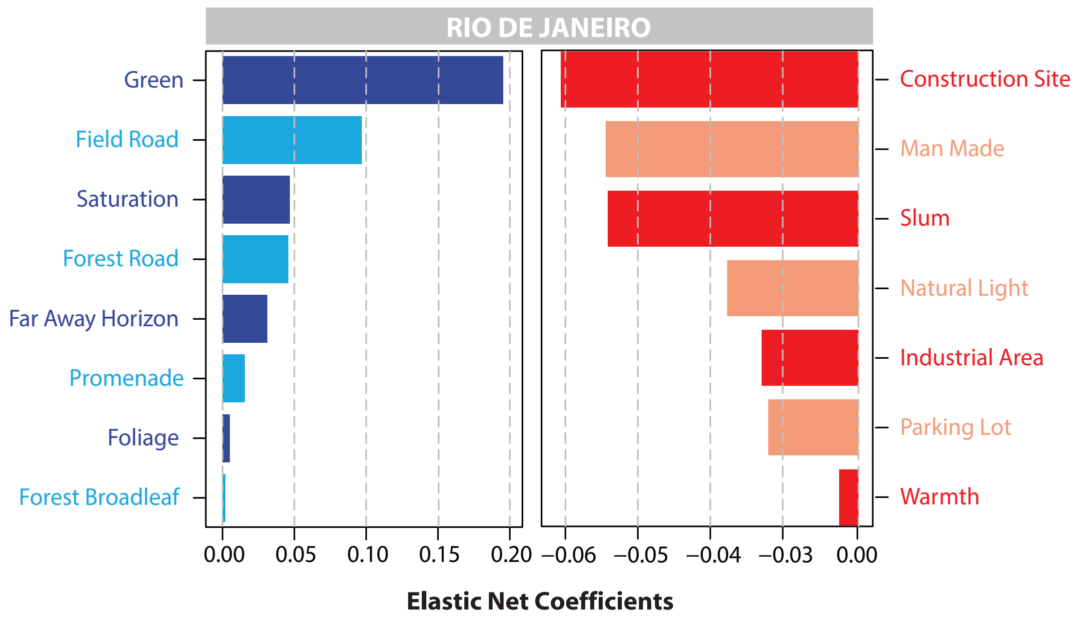


Figure 8.3. Elastic net coefficients to identify features that might be most relevant for understanding scenicness in Rio de Janeiro.
We find similar characteristics to our Great Britain analysis coming out in Rio de Janeiro as being scenic, such as "Green", "Field Road" and "Forest Road". We also see the coastal "Promenade", a feature well known to be scenic in Rio de Janeiro, is associated with greater scenicness. Unscenic characteristics are also similar to Great Britain, such as "Construction Site", "Man-Made", "Industrial Area" and "Parking Lot". We also notice that the feature "Slum" leads to lower ratings for scenicness.

8.4 Discussion

We explore how the definition of scenicness might differ in a tropical setting with visual landscapes of different characteristics to Great Britain. We find many similar scenic features in our Rio de Janeiro model, particularly those that signify forest-like scenery abundant with trees, such as "Forest Road", "Foliage" and "Forest Broadleaf". Surprisingly, we do not see similar water features picked up in our Elastic Net analysis, such as "Coast", which we find in our Great Britain analysis. However, images of the ocean are most likely being picked up as "Promenade" in this analysis, as Rio de Janeiro's coastline is largely a built-up area. Furthermore, as images included in this analysis are from *Google Street View*, the sample of coastal images has been taken primarily from streets via *Google Street View* vehicles, and therefore might contain man-made objects such as buildings or highways. In contrast, our Great Britain image dataset, primarily sourced from *Geograph,* most likely contains more images taken from footpaths, and thus have the water feature primarily in view without surrounding man-made objects.

In terms of built-up features that are associated with greater scenicness, our Rio de Janeiro model only picks up "Promenade". This may well reflect the fact that the

Places 365 building descriptions (e.g. “Cottage”, “Castle”, “Tower”) are more descriptive of building types typically seen in North American and European cities, and so this finding should not be taken to imply that Rio de Janeiro’s architecture itself is not beautiful. As we sourced photos from *Google Street View* in 2016, prior to Google's “Rio: Beyond the Map” project (https://beyondthemap.withgoogle.com/en-us/beyond-the-map), our dataset might be missing many images covering the favelas, which may have not yet been documented widely on *Google Street View*. While many people associate favelas with violent crime and poverty, they also feature colourful buildings, data on which might enrich future analyses.

In terms of features associated with lower ratings of scenicness, our Rio de Janeiro model largely accords with the Great Britain model, where man-made objects such as “Construction Site”, “Industrial Area” and “Parking Lot” are most associated with lower scenicness. Unlike our Great Britain model, we do not see large areas of flat green spaces featuring as unscenic in Rio de Janeiro, most likely reflecting the hilly nature of the city. An analysis of a larger area of a country such as Brazil, rather than just a city, would be helpful to understand the similarities and differences in what people find beautiful across the globe.

Chapter 9
Conclusions and future directions

9.1 Key results

Data generated through our increasing interactions online is allowing us to measure human experiences on an unprecedented scale (King, 2011; Lazer et al., 2009; Moat et al., 2014; Watts, 2007). In this thesis, we argue that the arrival of new online datasets can enable us to quantify aspects of the visual environment that were previously costly and time-consuming to measure, but that might be crucial to our wellbeing, such as the beauty of our everyday environment (see also Seresinhe, Preis & Moat, 2015). Recent advances in computer vision, particularly in deep learning algorithms, are making it possible to extract insights from images at a far greater speed and accuracy than before (LeCun, Bengio & Hinton, 2015). In the research reported here, we show how these two developments present us with a novel opportunity to understand not only whether beautiful places have a significant impact on our wellbeing, but also to developer a broader understanding of what beautiful places are composed of – one that goes beyond the simple explanation “what is natural is beautiful”. We summarise the key results of our investigations below.

9.1.1 Can we predict the scenicness of new places?

For this research, we exploit crowdsourced data from the online game *Scenic-Or-Not*, where users rate random geotagged photographs of Great Britain on a scale of 1 – 10, where 10 indicates “very scenic” and 1 indicates “not scenic”. The *Scenic-Or-Not* database contains 217,000 images, originally sourced from *Geograph*, covering 92.5% of the 1 km grid squares of Great Britain. However, the scenicness of an area can vary considerably within each 1 km grid square. Thus, the ability to predict the scenicness of new images (e.g. for an entirely new area, or at a high resolution such as street level), is crucial to enable future social science studies to investigate the connection between the beauty of the environment and various measures that might be important to us – from our wellbeing to the economic prosperity of a city. In Chapter 3 and 4, we explore different methods – including the exploitation of crowdsourced data, and computer vision techniques such as deep learning – to estimate the scenicness of places for which we do not have existing scenic ratings.

In Chapter 3, we analyse geotagged images uploaded to *Flickr*, combined with crowdsourced geographic data from *OpenStreetMap,* in order to estimate the scenicness of an area. We validate our findings using crowdsourced ratings of scenicness from *Scenic-Or-Not*. Our findings suggest that crowdsourced data from sources such as *Flickr* and *OpenStreetMap* do indeed contain information that can inform estimates of how scenic an area is. Specifically, we find that models using crowdsourced data can generate more accurate estimates of scenicness than models that use only basic census measurements such as population density or whether an area is urban or rural.

However, the improvements are modest, and more accurate in rural than in urban or suburban neighbourhoods. This may be due to a few different factors: one could be that people upload photographs to *Flickr* for a variety of reasons, for instance to create a memory of an event such as a birthday party or a sporting event. Such photos are less likely to be accurate representations of the environment in general. In addition, our algorithm that identifies whether images are taken outdoors is not perfect, and therefore we are likely to have a number of misidentified indoor images in our analysis, particularly in urban and suburban areas where building density is high. We therefore conclude that while crowdsourced data does seem to provide valuable information on how people perceive their everyday environments, we still need to find a more accurate way to estimate the scenicness of the environment.

In Chapter 4, we exploit recent advances in computer vision methods, particularly convolutional neural networks (CNNs), in order to evaluate to what degree of accuracy we can create a CNN to predict the beauty of scenes. We use a transfer learning approach to modify the existing Places365 CNN, which can already successfully detect the category of scenes, in order to train a new CNN, the Scenic-Or-Not CNN, to predict the scenicness of images. Training the Scenic-Or-Not CNN with over 160,000 images rated for scenicness from *Scenic-Or-Not* results in a high level of accuracy – 0.658 for all images and 0.590 for urban built-up images (as measured by the Kendall's Rank correlation between the predicted scenic scores and the actual scenic scores).

However, each image from *Scenic-Or-Not* (primarily sourced from *Geograph*, an online crowdsourcing project that aims to collate geographically-representative images of every square kilometre of the British Isles) may not fully represent the area in which it is taken, as scenicness can vary considerably within each square kilometre. Generating scenic ratings at a higher resolution might help us in studies where we want to understand the connection between scenicness and wellbeing in areas where scenicness varies considerably on a small scale, such as high-density urban areas. We therefore further train a new CNN, Street-View-Scenic CNN, on top of our previous Scenic-Or-Not CNN, using around 5,500 images rated for scenicness from *Google Street View.* With the Street-View-Scenic CNN, we achieve a performance score of 0.435 (the Kendall's Rank correlation between the predicted scenic scores and the actual scenic scores) for *Google Street View* images. This lower score might be due to the fact that *Google Street View* images are often of a lower quality than Geograph images, being composites that often contain image artefacts such as blurred areas, and which are shot with a wider angle of view. Further extensive training using a larger dataset of labelled *Google Street View* images should help to improve prediction accuracy.

Nonetheless, we have demonstrated that online data combined with neural networks can help quantify the beauty of the visual environment at an unprecedented scale.

9.1.2 What is the connection between scenicness and wellbeing?

Prior research has revealed that the connection between the environment and our wellbeing might vary depending on what aspect of wellbeing we measure. For example, White et al. (2013b) found that individuals report less mental distress when living nearer to the coast, but they did not find a similar association with life satisfaction. Therefore, in Chapter 5 and 6, we explore the connection between beautiful scenery and different types of wellbeing: (1) our experienced wellbeing, as measured though happiness ratings submitted via the mobile phone app *Mappiness* (Mackerron & Mourato, 2013), and (2) our evaluative wellbeing, specifically life satisfaction and mental distress, as measured through the annual survey responses to The UK Household Longitudinal Study, Understanding Society (University of Essex, 2017).

In Chapter 5, we combine our *Scenic-Or-Not* ratings with happiness ratings from *Mappiness* (Mackerron & Mourato, 2013), a pioneering large-scale ESM study that collects UK-wide data via an Apple iOS smartphone app, to investigate whether individuals achieve greater levels of happiness when encountering more scenic environments during their everyday life experience. We also test whether this relationship holds in built-up environments, as opposed to natural habitats, after taking other environmental measures such as green space into account. We find that individuals are happier in more scenic locations, even when we account for a range of factors such as the activity the individual was engaged in at the time, weather conditions, whether it was the weekend, and the income of local inhabitants. Crucially, the relationship we find holds not only in natural environments, but in built-up areas too, even after controlling for the presence of green space.

In Chapter 6, we explore whether the connection between scenicness and wellbeing might also hold for measures of evaluative wellbeing, specifically mental distress and life satisfaction, using annual data from *Understanding Society*, the United Kingdom Household Longitudinal Study of over 40,000 households that explores a wide range of themes such as family life, education, employment, finance, health and wellbeing. We also investigate whether we can confirm the findings of our previous study, which provided initial evidence linking scenic environments and self-reported health (Seresinhe et al., 2015), using an individual-level metric of self-reported health. In this previous study, we had self-reported health ratings at one point in time only, and therefore we were unable to control for the potential confounding factor that healthy people might self-select to move to locations that are more scenic. As *Understanding Society* provides data on self-reported health measurements gathered over several years, we attempt to address this possible self-selection bias.

We find no evidence that people report better evaluative mental wellbeing (as measured by “mental distress” and “life satisfaction”) when living in more scenic locations. However, we are able to confirm our previous finding: people who live in more scenic areas do report better health, and we can demonstrate that this result is not due to healthy people choosing to move to more scenic places.

We suggest reasons for why we might see a connection between scenicness and everyday happiness and scenicness and self-reported health but no connection between scenicness and mental distress and life satisfaction. Even though individuals experience an initial increase in mental wellbeing when they are first exposed to a more scenic location (as evidenced by our happiness and scenicness study in Chapter 5), this may fade in time, possibly due to adaptation (Brickman, Coats & Jannoff-Bulman, 1978). When people answer questions related to their evaluative wellbeing, such as “how satisfied are you with your life?”, they may be focusing on central aspects of their life such as their current level of income (Schkade & Kahneman, 1994; Kahneman et al., 2006) rather that the scenicness of their local neighbourhood.

Why might we still see a connection between scenic environments and self-reported physical wellbeing? We hypothesise that while people may no longer notice how beautiful their surroundings are, particularly when asked to reflect on big questions about their lives such as one's life-satisfaction, attractive settings might still encourage people to continue to engage in more physical activity. After all, when deciding whether to go for a walk, it seems sensible that one would be more inclined to do so if the setting is beautiful. Research from Ball et al. (2001) suggests that people might participate in increased physical activity in friendly and attractive surroundings.

Our results provide evidence that the aesthetics of the environments that policymakers choose to build – or indeed demolish – may have consequences for our subjective wellbeing.

9.1.3 What are scenic places composed of?

We find that individuals report more happiness when visiting more scenic locations, and that residents of more scenic places report better health. Yet, what are these scenic places composed of? As the beauty of outdoor spaces has long been considered difficult to quantify due to its subjective nature, people tend to gravitate towards the assumption that scenic beauty is akin to natural scenes. In Chapter 7, we again exploit deep learning methods to extract hundreds of characteristics, including scene attributes and place categories, from our corpus of over 200,000 *Scenic-Or-Not* images in order to develop a broader understanding of beauty that goes beyond the simple explanation that beautiful places are synonymous with natural places.

We discover that the presence of natural features such as “Valley”, “Coast” and “Mountain” can lead to places being considered more scenic. In urban built-up areas, natural features such as “Canal Natural”, “Garden” and “Trees” are associated with greater scenicness. However, beauty isn't simply in the domain of the natural – characterful buildings, such as “Cottage” and “Castle”, as well as bridge-like structures, such as “Viaduct” and “Aqueduct”, can also lead to places being considered more scenic. As expected, we find that man-made features such as “Construction Site” and “Parking Lot” are associated with lower scenicness. Surprisingly, large areas of green space such as “Grass” and “Athletic Field” can also lead to lower scenic ratings. We also find that “No Horizon” and “Open Spaces” are also associated with lower scenicness.

In Chapter 8, we explore what might be considered beautiful in a setting remarkably different from Great Britain: the tropical coastal city of Rio de Janeiro in Brazil. We see a few similar themes of beauty emerging, where scenes abundant with trees, such as “Forest Road”, “Foliage” and “Forest Broadleaf” are considered to be scenic while man-made features such as “Construction Site”, “Industrial Area”, and “Parking Lot” are most associated with lower scenicness. Although Rio de Janeiro is well known for its tropical beaches, we do not see water features such as “Coast” being picked up as scenic. Instead, this seems to be picked up by the feature “Promenade”, perhaps reflecting the built-up nature of the coastline in Rio de Janeiro. An analysis of a larger area of a country such as Brazil, with a visual environment that is remarkably different to that of Great Britain, may yield more interesting results to help explain the similarities and differences in what we find beautiful across the globe.

The ability to crowdsource large amounts of data, combined with the advent of deep learning, has allowed us to develop a much broader understanding of beauty that goes beyond the old adage ‘natural is beautiful’.

9.2 Limitations

Capturing scenicness

A key advantage of our *Scenic-Or-Not* dataset is the ability to exploit data on scenicness at a scale as large as an entire country. However, one can argue that as our images from *Scenic-Or-Not* are at a 1 km resolution, each image may not be fully representative of the area in which it was taken. We attempt to provide a potential solution to this problem for future research by creating our Street-View-Scenic CNN, which can predict the scenicness of images sourced from *Google Street View*, thereby allowing scenic predictions at a much higher resolution. While further training of our Street-View-Scenic CNN is required to improve accuracy, it allows the possibility for researchers to gather scenic ratings for any area that contains *Google Street View* images. 360-degree views of locations would help to ensure that the true scenicness of an area has been captured, and to ensure that highly local features that could have an impact on the scenic rating of an area (such as a particular beautiful building, a local cluster of trees or an unsightly industrial structure), have not been missed out of the analysis. One final consideration is that *Google Street View* images do show some variation depending on the transient conditions under which they were taken, such as the weather or a vehicle obstructing the view. The ability to access historical data helps mitigate this, as we can retrieve multiple pictures of the same area under different conditions to ensure that we get closer to measuring what people might actually experience through their own repeated exposure to an area.

Effect size

While we find a connection between everyday happiness and scenicness, we recognize that the general benefit per individual being exposed to a more scenic area appears to be relatively small. As summarised in Chapter 5, the predicted increase in happiness of someone moving from a neighbourhood with the lowest scenicness rating of 1 to a neighbourhood with a scenicness rating in the top decile (i.e. a scenicness rating above 4.67), would be 1.130 points on the 0–100 happiness scale. This is slightly below the increase in happiness observed when participants are sleeping, resting or relaxing (1.133), and greater than the increase in happiness observed when moving from a built-up environment to a natural environment (0.574) or when moving from a suburban environment to a rural environment (0.608). While this effect is small, we argue that the impact of thousands or even millions of people visiting a scenic area is cumulatively very large, and thus has value for consideration in public policy.

Causation

We also acknowledge that our research has primarily looked at the association between scenicness and wellbeing, rather than establishing whether visiting more scenic places causes increased wellbeing. We have made several attempts to establish causation. Both our *Mappiness* and *Understanding Society* datasets have given us a great number of variables to control for, making us increasingly confident that the relationship we are capturing is indeed the effect of scenicness and not a potential confounding variable such as the effect of visiting a natural place, visiting a more affluent area, or the effect of relaxation. In our study on reported health, we control for the problem of reverse causality, and demonstrate that healthy people do not self-select to live in more scenic neighbourhoods.

We also address omitted variable bias (a bias introduced by failure to measure some factor that might be important to the study) by conducting our analyses using fixed effects models. Fixed effects models allow us to control for characteristics that do not change over time, whether they are measured or not, such as gender, ethnicity or genetic makeup (Allison, 2009). In the same vein, it would also be useful to calculate fixed effects for the regions used in our study, such as LSOAs, to capture any unobserved variables of that region that we may not have been able to capture in our previous analyses. We do account for several environmental variables, from green space to natural habits to measures of deprivation, but one could argue that we might still have failed to measure something in the environment that is crucial to the study. As we have only begun to collect historical data via

Google Street View, we have not been able to control for unobserved regional effects in this study. However, as we move to an era where we can rapidly measure characteristics of our environments, future research will be in a position to account for this as well.

9.3 Implications for policy, and future directions

We find that individuals are happier when visiting more scenic locations, even when accounting for a wide range of factors such as the activity the individual was engaged in at the time, weather conditions, whether it was the weekend, and the income of local inhabitants. However, we do not find evidence that people who live in more scenic locations, rather than simply visiting them, report less mental distress or increased life satisfaction.

Our results could indicate that people who move to more scenic areas might, in time, adapt to their beautiful surroundings, which then no longer play a part when asked to reflect on their wellbeing. This accords with the concept of the "hedonic treadmill", the first convincing empirical evidence of which was published by Brickman, Coats & Jannoff-Bulman (1978), where they found that lottery winners, even after initially feeling very good about their winnings, after some time had passed did not appear to be much happier than a control group. This also accords with the well-known study "Does Living in California Make People Happy" by Schkade and Kahneman (1994), where students living in California – well known for its pleasant climate and beautiful beaches – did not report higher life satisfaction compared to their Midwest counterparts. The authors argue that when asking people specifically to reflect on their life satisfaction, their focus is more on the central aspects of their lives rather than on other general factors that might also be important to them, such as a great climate. Schkade and Kahneman (1994) claim that what is important to you simply depends on what you are focusing on at the time.

This, however, does not preclude individuals from still gaining the benefits that scenic environments might provide for the long term. We reconfirm our initial findings (Seresinhe et al., 2015) with an even more robust analysis: that people who live in more scenic surroundings do report better health. With this newer version of the study, we use a fixed affects approach, controlling for an even wider range of factors such as household income, marital status and residence type (e.g. detached, terraced). We also address potential self-selection bias, and demonstrate that while healthier people might be more likely to move, they do not choose to move primarily to more scenic locations.

The fact that we still see people report better health in scenic locations might be due to the fact that more beautiful environments are encouraging people to live more active lifestyles by partaking in more physical outdoors activities. Physical inactivity costs the NHS in England more than £450 million a year (Public Health England, 2016). Further research investigating the link between scenic areas and outdoor activity could be highly valuable for policymakers. To further understand the relationship between people's reported health and scenic environments, it would also be valuable to directly study the link between scenic areas and measures of actual health (not just self-reported health).

As we do indeed find a connection between scenic places and everyday happiness, public policy could also consider interventions in places that are likely to affect our everyday lives, for example considering the design of green places in areas in which people live or work, or interventions in areas with high volumes of traffic that people might pass as they commute to work. Our study exploring the composition of beautiful places reveals interesting insights to help inform how we might design spaces to increase human wellbeing: flat and uninteresting green spaces are not necessarily beautiful. Green spaces that contain “trees” and “valley” contours are more pleasing to the eye and may, in turn, be more pleasing to spend time in. Characterful buildings and stunning architectural features can lead to more city beauty, while closed-off places that offer no views, as well as wide-open places that are flat and offer no refuge, are places that we least prefer.

Finally, while our primary focus has been on wellbeing, future research could investigate another area important to public policy: driving investment into local areas (Harvey & Julian, 2015). Studies that investigate the connection between scenicness and the economic value of a city – from house prices to commercial property values or even improvements in high street trading – would be highly valuable research to undertake, as increases in trading and changes in property values can have clear benefits to the local economy, such as increased income to local businesses and local governments.

9.4 Discussion

Our findings demonstrate that the availability of large crowdsourced datasets, coupled with recent advances in neural networks, can help us develop a deeper understanding of what environments we find beautiful. As we discover that beauty is not simply synonymous with nature, it no longer needs to be the case that to seek beauty we must flee to the countryside; we might also be able to find beauty in the cities in which most of us live. Recent advances in neural networks will also inevitably bring a lot of change to our cityscapes. For example, neural networks have been instrumental in driving the development of autonomous vehicles, which are very likely to dramatically change how we design our future cities, for example by reducing the need for car parks and allowing the development of more efficient road networks. It feels well timed that this research has taken initial steps to develop methods to help us understand what might make our future cities more beautiful. We have also developed methods that allow us to infer the beauty of places at high resolution, which can aid policymakers in the identification of areas that might be in most need of infrastructure investment.

Crucially, our findings also take an important step towards providing evidence that the beauty of the environments in which people visit and live, and therefore decisions made about their creation or preservation, might have a vital impact on people's everyday wellbeing. With such evidence that beautiful environments are in fact linked to our happiness and reported health, we argue that we can no longer afford to assume that scenic beauty is no more important than a mere luxury. Instead, our research provides evidence that suggests that beautiful environments may be an essential component of human wellbeing.

References

Akay, A., B Bargain, O. & Jara Tamayo, H. (2017) *Back to Bentham, should we? Large-scale comparison of experienced versus decision utility, GLO discussion paper, No. 52*. Global Labor Organization (GLO), Maastricht University. [online] Available from: http://hdl.handle.net/10419/156693 (Accessed 31 January 2018).

Akbar, K. F., Hale, W. H. G. & Headley, A. D. (2003) Assessment of scenic beauty of the roadside vegetation in northern England. *Landscape and Urban Planning*, 63 (3): 139-144.

Alanyali, M., Moat, H. S. & Preis, T. (2013) Quantifying the relationship between financial news and the stock market. *Scientific Reports,* 3: 3578.

Alanyali, M., Preis, T. & Moat, H. S. (2016) Tracking protests using geotagged Flickr photographs. *PLOS ONE*: 11 (3): e0150466.

Alcock, I., White, M. P., Lovell, R., Higgins, S. L., Osborne, N. J., Husk, K. & 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.

Alexander, C. (1977) *A pattern language: Towns, buildings, construction*. New York: Oxford University Press.

Alis, C. M., Lim, M. T., Moat, H. S., Barchiesi, D., Preis, T. & Bishop, S. R. (2015) Quantifying regional differences in the length of Twitter messages. *PLOS ONE*: 10 (4): e0122278.

Allin, P. & Hand, D. J. (2017) New statistics for old?—measuring the wellbeing of the UK. *Journal of the Royal Statistical Society A*, 180 (1): 1-22.

Allison, P. (2009) *Fixed effects regression models*. London: Sage.

Antoniou, V., Morley, J. & Haklay, M. (2010) Web 2.0 geotagged photos: Assessing the spatial dimension of the phenomenon. *Geomatica*, 64 (1): 99-110.

Appleton, J. (1975) *The experience of landscape*. London: Wiley.

Arriaza, M., Canas-Ortega, J. F., Canas-Madueno, J. A. & Ruiz-Aviles, P. (2004) Assessing the visual quality of rural landscapes. *Landscape and Urban Planning*, 69 (1): 115-125.

Arthur, L. M. (1977) Predicting scenic beauty of forest environments: some empirical tests. *Journal of Forest Science*, 23 (2): 151-160.

Bakhshi, H. (2010) *Beauty: value beyond measure*. London: Commission for Architecture and the Built Environment.

Bakshy, E., Messing, S. & Adamic, L. A. (2015) Exposure to ideologically diverse news and opinion on Facebook. *Science*, 348 (6239): 1130.

Ball, K., Bauman, A., Leslie, E. & Owen, N. (2001) Perceived environmental aesthetics and convenience and company are associated with walking for exercise among Australian adults. *Preventive Medicine*, 33 (5): 434-440.

Barchiesi, D., Moat, H. S., Alis, C., Bishop, S. & Preis, T. (2015a) Quantifying international travel flows using Flickr. *PLOS ONE*: 10 (7): e0128470.

Barchiesi, D., Preis, T., Bishop, S. & Moat, H. S. (2015b) Modelling human mobility patterns using photographic data shared online. *Royal Society Open Science*: 2 (8): 150046.

Batty, M. (2013) Big data, smart cities and city planning. *Dialogues in Human Geography*, 3 (3): 274-279.

Bentham, J. (2005) A comment on the commentaries and a fragment on government. In: Burns, J. H. & Hart, H. L. A. (eds.) *The Collected Works of Jeremy Bentham*. Oxford: Oxford University Press:

Berlyne, D. E. (1971) *Aesthetics and Psychobiology*. New York: Appleton-Century-Crofts.

Besag, J. (1974) Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society, Series B*, 36 (2): 192-236.

Besag, J., York, J. & Mollié, A. (1991) Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*, 43 (1): 1-20.

Bishop, I. D. & Hulse, D. W. (1994) Prediction of scenic beauty using mapped data and geographic information systems. *Landscape and Urban Planning*, 30 (1-2): 59-70.

Bivand, R. S., Pebesma, E. & Gómez-Rubio, V. (2013) *Applied spatial data analysis with R*. New York: Springer.

Bollen, J., Mao, H. & Zeng, X. (2011) Twitter mood predicts the stock market. *Journal of Computer Science*, 2 (1): 1-8.

Bond, L., Kearns, A., Mason, P., Tannahill, C., Egan, M. & Whitely, E. (2012a) Exploring the relationships between housing, neighbourhoods and mental wellbeing for residents of deprived areas. *BMC Public Health*, 12 (1): 48.

Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. & Fowler, J. H. (2012b) A 61-million-person experiment in social influence and political mobilization. *Nature*, 489 (7415): 295-298.

Botta, F., Moat, H. S. & Preis, T. (2015) Quantifying crowd size with mobile phone and Twitter data. *Royal Society Open Science*, 2 (5): 150162.

Bratman, G. N., Daily, G. C., Levy, B. J. & Gross, J. J. (2015a) The benefits of nature experience: Improved affect and cognition. *Landscape and Urban Planning*, 138: 41-50.

Bratman, G. N., Hamilton, J. P., Hahn, K. S., Daily, G. C. & Gross, J. J. (2015b) Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proceedings of the National Academy of Sciences of the United States of America*, 112 (28): 8567-8572.

Brickman, P., Coates, D. & Janoff-Bulman, R. (1978) Lottery winners and accident victims: Is happiness relative? *Journal of Personality and Social Psychology*, 36 (8): 917-927.

Cameron, D. (2010) *PM's speech on wellbeing*. [online] Available from: https://www.gov.uk/government/speeches/pm-speech-on-wellbeing (Accessed 31 January 2018).

Carmona, M., Heath, T., Oc, T. & Tiesdell, S. (2003) *Public places, urban spaces: The dimensions of urban design*. Abingdon: Routledge.

Casalegno, S., Inger, R., DeSilvey, C. & Gaston, K. J. (2013) Spatial covariance between aesthetic value & other ecosystem services. *PLOS ONE*, 8 (6): e68437.

Choi, H. & Varian, H. (2012) Predicting the Present with Google Trends. *Economic Review*, 88: 2-9.

Curme, C., Preis, T., Stanley, H. E. & Moat, H. S. (2014) Quantifying the semantics of search behavior before stock market moves. *Proceedings of the National Academy of Sciences*, 111 (32): 11600-11605.

Curme, C., Zhuo, Y. D., Moat, H. S. & Preis, T. (2017) Quantifying the diversity of news around stock market moves. *Journal of Network Theory in Finance*: 3 (1): 1-20.

Crowley, E. J. & Zisserman, A. (2014) In search of art. In: *Computer Vision-ECCV 2014 Workshops, 6 - 12 September 2014, Zurich, Switzerland*. New York: Springer: pp. 54-70.

DCLG. (2007) *Generalised Land Use Database Statistics for England 2005*. London: DCLG.

De Nadai, M., Vieriu, R. L., Zen, G., Dragicevic, S., Naik, N., Caraviello, M., Hidalgo, C. A., Sebe, N. & Lepri, B. (2016) Are safer looking neighborhoods more lively? A multimodal investigation into urban life. In: *Proceedings of the 2016 ACM on Multimedia Conference, 15 - 19 October 2016, Amsterdam, The Netherlands*. New York: ACM: pp. 1127-1135.

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., 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.

Department for Communities and Local Government. (2007) *Generalised land use database statistics for England 2005*. London: Department for Communities and Local Government.

Department for Communities and Local Government. (2011) *English indices of deprivation 2010*. London: Department for Communities and Local Government.

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 (2): 409-427.

Donahue, J., Jia, Y., Vinyals, O., Hoffman, J., Zhang, N., Tzeng, E. & Darrell, T. (2014) DeCAF: A deep convolutional activation feature for generic visual recognition. In: *International Conference in Machine Learning, 21 - 26 June 2014, Beijing, China*. San Francisco: Morgan Kaufmann Publishers Inc.: pp. 647-655.

Dosen, A. S. & Ostwald, M. J. (2016) Evidence for prospect-refuge theory: a meta-analysis of the findings of environmental preference research. *City, Territory and Architecture*, 3 (1).

Dubey, A., Naik, N., Parikh, D., Raskar, R. & Hidalgo, C. A. (2016) Deep learning the city: Quantifying urban perception at a global scale. In: *European Conference on Computer Vision, 8 - 16 October 2016, Amsterdam, The Netherlands*. New York: Springer: pp. 196-212.

Dunkel, A. (2015) Visualizing the perceived environment using crowdsourced photo geodata. *Landscape and Urban Planning*, 142: 173-186.

Dykes, J., Purves, R., Edwardes, A. & Wood, J. (2008) Exploring volunteered geographic information to describe place: visualization of the ‘Geograph British Isles’ collection. In: *Proceedings of the GIS Research UK 16th Annual Conference GISRUK, 2 - 4 April 2008, Manchester, UK*. Manchester: Manchester Metropolitan University: pp. 256-267.

Eco, U. (2004) *On beauty*. New York: Secker & Warburg.

Ellaway, A., Macintyre, S. & Bonnefoy, X. (2005) Graffiti, greenery, and obesity in adults: secondary analysis of European cross sectional survey. *BMJ*, 331 (7517): 611-612.

Enquist, M. & Arak, A. (1994) Symmetry, beauty and evolution. *Nature*, 372: 169-172.

Experian. (2011) *Household income 2011*. Nottingham: Experian.

Ferrer-i-Carbonell, A. & Gowdy, J. M. (2007) Environmental degradation and happiness. *Ecological Economics*, 60 (3): 509-516.

Flickr API. (2013) *Flickr photographs data*. [online] Available from: https://www.flickr.com/services/api/flickr.photos.search.html (Accessed throughout 2014).

Galindo, M. P. G. & Rodriquez, J. A. C. (2000) Environmental aesthetics and psychological wellbeing: relationships between preference judgements for urban landscapes and other relevant affective responses. *Psychology in Spain*, 4 (1): 13-27.

GeoFabrik. (2016) *OpenStreetMap data on buildings, points of interest and natural points of interest*. [online] Available from: http://www.geofabrik.de (Accessed 20 July 2016).

Gilchrist, K., Brown, C. & Montarzino, A. (2015) Workplace settings and wellbeing: Greenspace use and views contribute to employee wellbeing at peri-urban business sites. *Landscape and Urban Planning*, 138: 32-40.

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S. & Brilliant, L. (2008) Detecting influenza epidemics using search engine query data. *Nature*, 457 (7232): 1012-1014.

Girardin, F., Calabrese, F., Dal Fiore, F., Ratti, C. & Blat, J. (2008) Digital footprinting: Uncovering tourists with user-generated content. *IEEE Pervasive Computing*, 7 (4): 36-43.

Gliozzo, G., Pettorelli, N. & Haklay, M. M. (2016) Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. *Ecology and Society*, 21 (3): 6.

Goodchild, M. F. (2007) Citizens as sensors: the world of volunteered geography. *GeoJournal*, 69 (4): 211-221.

Graham, M. & Shelton, T. (2013) Geography and the future of big data, big data and the future of geography. *Dialogues in Human Geography*, 3 (3): 255-261.

Grêt-Regamey, A., Bishop, I. D. & Bebi, P. (2007) Predicting the scenic beauty value of mapped landscape changes in a mountainous region through the use of GIS. *Environment and Planning B: Planning and Design*, 34 (1): 50-67.

Haklay, M. (2010) How good is volunteered geographical information? A comparative study of OpenStreetMap and Ordnance Survey datasets. *Environment and Planning B: Planning and Design*, 37 (4): 682-703.

Haklay, M., Singleton, A. & Parker, C. (2008) Web Mapping 2.0: The neogeography of the GeoWeb. *Geography Compass*, 2 (6): 2011-2039.

Harris, R., Sleight, P. & Webber, R. (2005) *Geodemographics, GIS, and neighbourhood targeting*. *Mastering GIS.* Chichester: Wiley.

Hartig, T., Evans, G. W., Jamner, L. D., Davis, D. S. & Gärling, T. (2003) Tracking restoration in natural and urban field settings. *Tracking restoration in natural and urban field settings*, 23 (2): 109-123.

Harvey, A. & Julian, C. (2015) *A Community Right to Beauty: Giving communities the power to shape, enhance and create beautiful places, buildings and spaces*. Respublica. [online] Available from: https://www.respublica.org.uk/our-work/publications/a-community-right-to-beauty-giving-communities-the-power-to-shape-enhance-and-create-beautiful-places-developments-and-spaces/ (Accessed 31 January 2018).

Hastie, T., J., Tibshirani, R. J. & Friedman, J. H. (2009) *The elements of statistical learning: data mining, inference, and prediction*. New York: Springer.

He, K., Zhang, X., Ren, S. & Sun, J. (2016) Deep residual learning for image recognition. In: *IEEE conference on computer vision and pattern recognition, 26 June - 1 July 2016, Las Vegas, Nevada*. IEEE: pp. 770-778.

Hektner, J. M., Schmidt, J. A. & Csikszentmihalyi, M. (2007) *Experience sampling method: Measuring the quality of everyday life*. London: Sage.

Helliwell, J. F. & Barrington-Leigh, C. P. (2010) Viewpoint: Measuring and understanding subjective well-being. *Canadian Journal of Economics*, 43 (3): 729-753.

Herzog, T. R. & Chernick, K. K. (2000) Tranquility and danger in urban and natural settings. *Journal of environmental psychology*, 20 (1): 29-39.

Herzog, T. R., Colleen, Maguire, P. & Nebel, M. B. (2003) Assessing the restorative components of environments. *Journal of Environmental Psychology*, 23 (2): 159-170.

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): 460.

Hull, R. B. & Harvey, A. (1989) Explaining the emotion people experience in suburban parks. *Environment and Behavior*, 21 (3): 323-345.

Humpel, N., Owen, N., Iverson, D., Leslie, E. & Bauman, A. (2004) Perceived environment attributes, residential location, and walking for particular purposes. *American Journal of Preventive Medicine*, 26 (2): 119-125.

Ipsos MORI (2010) People and places: public attitudes to beauty. *On behalf of the Commission for Architecture and the Built Environment (CABE).*,

James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013) *An introduction to statistical learning*. New York: Springer.

Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S. & Darrell, T. (2014) Caffe: Convolutional architecture for fast feature embedding. In: *Proceedings of the 22nd ACM international conference on Multimedia, 03 - 07 November 2014, Orlando, Florida*. New York: ACM: pp. 675-678.

Joye, Y. (2007) Architectural lessons from environmental psychology: The case of biophilic architecture. *Review of General Psychology*, 11 (4): 305-328.

Kabkab, M., Hand, E., & Chellappa, R. (2016) On the size of convolutional neural networks and generalization performance. In: *23rd International Conference on Pattern Recognition (ICPR), 4-8 December 2016, Cancun, Mexico*. IEEE: pp. 3572-3577.

Kahle, D. & Wickham, H. (2013) ggmap: spatial visualization with ggplot2. *The R Journal*, 5 (1): 144-161.

Kahneman, D. & Riis, J. (2005) Living, and thinking about it: Two perspectives on life. In: Felicia A. Huppert, Baylis, N. & Keverne, B. (eds.) *The Science of Well-Being*. 285-301.

Kahneman, D. & Deaton, A. (2010) High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, 107 (38): 16489.

Kahneman, D., Krueger, A. B., Schkade, D., Schwarz, N. & Stone, A. A. (2006)

Would you be happier if you were richer? A focusing illusion. *Science*, 312 (5782): 1908-1910.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N. & Stone, A. A. (2004) A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306 (5702): 1776-1780.

Kahneman, D. & Thaler, R. H. (2006) Anomalies: Utility maximization and experienced utility. *Journal of Economic Perspectives*, 20 (1): 221-234.

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*. Cambridge: Cambridge University Press.

Kaplan, S. (1987) Aesthetics, Affect, and Cognition: Environmental Preference from an Evolutionary Perspective. *Environment and Behavior*, 19 (1): 3-32.

Kaplan, S. (1995) The restorative benefits of nature: Toward an integrative framework. *Journal of Environmental Psychology*, 15 (3): 169-182.

Kaplan, S., Kaplan, R. & Wendt, J. S. (1972) Rated preference and complexity for natural and urban visual material. *Perception & Psychophysics*, 12 (4): 354-356.

Kardan, O., Gozdyra, P., Misic, B., Moola, F., Palmer, L. J., Paus, T. & Berman, M. G. (2015) Neighborhood greenspace and health in a large urban center. *Scientific Reports*, 5: 11610.

Kellert, S. R. & Wilson, E. O. (1995) *The biophilia hypothesis*. Washington DC: Island Press.

King, G. (2011) Ensuring the data-rich future of the social sciences. *Science*, 331 (6018): 719-721.

Kristoufek, L., Moat, H. S. & Preis, T. (2016) Estimating suicide occurrence statistics using Google Trends. *EPJ Data Science*: 5 (1): 32.

Krizhevsky, A., Sutskever, I. & Hinton, G. E. (2012) ImageNet classification with deep convolutional neural networks. In: Pereira, F., Burges, C. J. C., Bottou, L. & Weinberger, K. Q. (eds.) *Advances in Neural Information Processing Systems 25, 3 - 8 December 2012, Lake Tahoe, Nevada*. New York: Curran Associates, Inc.: pp. 1097-1105.

Küller, R. (1972) *A semantic model for describing perceived environment*. Stockholm: National Swedish Institute for Building Research.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D. & Van, A., Marshall (2009) Computational social science. *Science*, 323 (5915): 721-723.

LeCun, Y., Bottou, L., Bengio, Y. & Haffner, P. (1998) Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86 (11): 2278-2324.

LeCun, Y., Bengio, Y. & Hinton, G. (2015) Deep learning. *Nature*, 521 (7553): 436-444.

Lelkes, O. (2006) Knowing what is good for you: Empirical analysis of personal preferences and the “objective good”. *Journal of Socio-Economics*, 35 (2): 285-307.

Letchford, A. (2016) *Streetview Python Module*. [online] Available from: https://github.com/robolyst/streetview (Accessed 23 February 2017).

Letchford, A., Preis, T. & Moat, H. S. (2016) Quantifying the search behaviour of different demographics using Google Correlate. *PLOS ONE*: 11 (2): e0149025.

Loewen, L. J., Steel, G. D. & Suedfeld, P. (1993) Perceived safety from crime in the urban environment. *Journal of Environmental Psychology*, 13 (4): 323-331.

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 (7): 587-592.

MacKerron, G. & Mourato, S. (2013) Happiness is greater in natural environments. *Global Environmental Change*, 23 (5): 992-1000.

Met Office. (2006) *MIDAS: UK hourly rainfall data*. NCAS British Atmospheric Data Centre. [online] Available from: http://catalogue.ceda.ac.uk/uuid/bbd6916225e7475514e17fdbf11141c1 (Accessed 28 June 2016).

Met Office. (2006) *MIDAS: UK Hourly Weather Observation Data*. NCAS British Atmospheric Data Centre. [online] Available from: http://catalogue.ceda.ac.uk/uuid/916ac4bbc46f7685ae9a5e10451bae7c (Accessed 28 June 2016).

Mitchell, R. & Popham, F. (2007) Greenspace, urbanity and health: relationships in England. *Journal of Epidemiology and Community Health*, 61 (8): 681-683.

Mitchell, R. & Popham, F. (2008) Effect of exposure to natural environment on health inequalities: an observational population study. *Lancet*, 372 (9650): 1655-1660.

Moat, H. S., Curme, C., Avakian, A., Kenett, D. Y., Stanley, H. E. & Preis, T. (2013) Quantifying Wikipedia usage patterns before stock market moves. *Scientific Reports*, 3: 1801.

Moat, H. S., Curme, C., Stanley, H. E., & Preis, T. (2014) Anticipating stock market movements with Google and Wikipedia. In D. Matrasulov, & H. E. Stanley (Eds.), *Nonlinear Phenomena in Complex Systems: From Nano to Macro Scale,* pp. 47-59*.* Amsterdam: Springer.

Moat, H. S., Olivola, C. Y., Chater, N. & Preis, T. (2016) Searching choices: quantifying decision-making processes using search engine data. *Topics in Cognitive Science*: 8 (3): 685-696.

Moat, H. S., Preis, T., Olivola, C. Y., Liu, C. & Chater, N. (2014) Using big data to predict collective behavior in the real world. *Behavioral and Brain Sciences*, 37 (1): 92-93.

Morton, D., Rowland, C., Wood, C., Meek, L., Marston, C., Smith, G., Wadsworth, R. & Simpson, I. (2014) *Land Cover Map 2007 (25m raster, GB) v1.2.* NERC Environmental Information Data Centre. [online] Available from: https://doi.org/10.5285/a1f88807-4826-44bc-994d-a902da5119c2 (Accessed 12 May 2016).

Munroe, R. (2010) *Colour Survey Results*. [online] Available from: http://blog.xkcd.com/2010/05/03/color-survey-results/ (Accessed May 29).

Naik, N., Philipoom, J. & Raskar…, R. (2014) Streetscore-predicting the perceived safety of one million streetscapes. In: *IEEE Conference on Computer Vision and Pattern Recognition Workshops, 23-28 June 2014, Colombus, Ohio*. Washington DC: IEEE Computer Society: pp. 793-799.

Nasar, J. L. (1994) Urban design aesthetics: The evaluative qualities of building exteriors. *Environment and Behavior*, 26 (3): 377-401.

National Records of Scotland. (2012) *Scotland's census 2011*. [online] Available from: http://www.scotlandscensus.gov.uk/ (Accessed 16 July 2014).

Neis, P. & Zipf, A. (2012) Analyzing the contributor activity of a volunteered geographic information project — The case of OpenStreetMap. *ISPRS International Journal of Geo-Information*, 1 (2): 146-165.

Noguchi, T., Stewart, N., Olivola, C. Y., Moat, H. S. & Preis, T. (2014) Characterizing the time-perspective of nations with search engine query data. *PLOS ONE*: 9 (4): e95209.

Nov, O., Naaman, M. & Ye, C. (2008) What drives content tagging: the case of photos on Flickr. In: *2008 Conference on Human Factors in Computing Systems, 5-10 April 2008, Florence, Italy*. New York: ACM: pp. 1097-1100.

O'Brien, O., Cheshire, J. & Batty, M. (2014) Mining bicycle sharing data for generating insights into sustainable transport systems. *Journal of Transport Geography*, 34: 262-273.

O'Donnell, G., Deaton, A., Durand, M., Halpern, D. & Layard, R. (2014) *Well-being and policy*. London: Legatum Institute.

Office for National Statistics. (2012) *2011 census data for England and Wales*. [online] Available from: https://www.nomisweb.co.uk/census/2011 (Accessed 16 July 2014).

Office for National Statistics. (2013) *The 2011 rural-urban classification for small area geographies*. [online] Available from: http://geoportal.statistics.gov.uk/ (Accessed 16 July 2014).

Orians, G. H. & Heerwagen, J. H. (1992) Evolved responses to landscapes. In: Barkow, J. H., Cosmides, L. & Tooby, J. (eds.) *Evolutionary psychology and the generation of culture*. New York: Oxford University Press: 555-579.

Palmer, J. F. (2004) Using spatial metrics to predict scenic perception in a changing landscape: Dennis, Massachusetts. *Landscape and Urban Planning*, 69 (2-3): 201-218.

Pan, S. J. & Yang, Q. (2010) A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22 (10): 1345-1359.

Parliamentary Office of Science and Technology. (2016) *Green space and health, POSTnote 538*. London: Parliamentary Office of Science and Technology.

Patterson, G., Xu, C., Su, H. & Hays, J. (2014) The SUN attribute database: beyond categories for deeper scene understanding. *International Journal of Computer Vision*, 108 (1): 59-81.

Pesaran, M. H. & Zhou, Q. (2018) Estimation of time-invariant effects in static panel data models. *Econometric Reviews*, 37 (10): 1137-1171.

Porteous, J. D. (2013) *Environmental aesthetics: Ideas, politics and planning*. Abingdon: Routledge.

Preis, T., Moat, H. S., Stanley, H. E. & Bishop, S. R. (2012) Quantifying the advantage of looking forward. *Scientific Reports*, 2: 350.

Preis, T., Moat, H. S., Bishop, S. R., Treleaven, P. & Stanley, H. E. (2013) Quantifying the digital traces of Hurricane Sandy on Flickr. *Scientific Reports*, 3: 3141.

Preis, T., Moat, H. S. & Stanley, H. E. (2013) Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports*, 3: 1684.

Preis, T. and Moat, H. S. (2014) Adaptive nowcasting of influenza outbreaks using Google searches. *Royal Society Open Science*: 1 (2): 140095.

Preis, T. & Moat, H. S. (2015). Early signs of financial market moves reflected by Google searches. In Gonçalves, B. & Perra, N. (eds.) *Social Phenomena: From Data Analysis to Models*. Amsterdam: Springer: pp. 89-102.

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 (5): 319-337.

Public Health England. (2016) *Physical inactivity: economic costs to NHS clinical commissioning groups*. [online] Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/524234/Physical_inactivity_costs_to_CCGs.pdf (Accessed 20 March 2018).

Purves, R., Edwardes, A. & Wood, J. (2011) Describing place through user generated content. *First Monday*, 16 (9).

Quercia, D. (2013) Urban*: Crowdsourcing for the good of London. In: *22nd International World Wide Web Conference, 13 - 17 May 2013, Rio de Janeiro, Brazil*. New York: ACM: pp. 591-592.

Quercia, D., O'Hare, N. K. & Cramer, H. (2014) Aesthetic capital: What makes London look beautiful, quiet, and happy. In: *Proceedings of the 17th ACM conference on computer supported cooperative work & social computing, 15 - 19*

February 2014, Baltimore, Maryland. New York: ACM: pp. 945-955.

Ratliff, F. (1976) On the Psychophysiological Bases of Universal Color Terms. *Proceedings of the American Philosophical Society*, 120 (5): 311-330.

Real, E., Arce, C. & Manuel Sabucedo, J. (2000) Classification of landscapes using quantitative and categorical data, and prediction of their scenic beauty in North-Western Spain. *Journal of Environmental Psychology*, 20 (4): 355-373.

Reber, R., Schwarz, N. & Winkielman, P. (2004) Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience? *Personality and Social Psychology Review*, 8 (4): 364-382.

Redelmeier, D. A. & Kahneman, D. (1996) Patients' memories of painful medical treatments: Real-time and retrospective evaluations of two minimally invasive procedures. *Pain*, 66 (1): 3-8.

Rehdanz, K. & Maddison, D. (2005) Climate and happiness. *Ecological Economics*, 52 (1): 111-125.

Reynolds, F. (2015) *Urbanisation and why good planning matters. The Fight for Beauty.* London: Oneworld Publications.

Richards, J., Jiang, X., Kelly, P., Chau, J., Bauman, A. & Ding, D. (2015) Don't worry, be happy: cross-sectional associations between physical activity and happiness in 15 European countries. *BMC Public Health*, 15 (1): 1-8.

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.

Roberst-Hughes, R. (2013) *City Health Check: How design can save lives and money*. London: Royal Institute of British Architects (RIBA).

Salesses, P., Schechtner, K. & Hidalgo, C. A. (2013) The collaborative image of the city: Mapping the inequality of urban perception. *PLOS ONE*, 8 (7): e68400.

Scenic-Or-Not. (2014) *Scenic ratings*. [online] Available from: http://scenic.mysociety.org (Accessed 2 August 2014).

Schirpke, U., Tasser, E. & Tappeiner, U. (2013) Predicting scenic beauty of mountain regions. *Landscape and Urban Planning*, 111 (1): 1-12.

Schkade, D. A. & Kahneman, D. (1998) Does living in California make people happy? A focusing illusion in judgments of life satisfaction. *Psychological Science*, 9 (5): 340-346.

Scottish Government. (2012) *2011-2012 urban rural classification*. [online] Available from: http://www.gov.scot/Topics/Statistics/About/Methodology/UrbanRuralClassification/Urban-Rural-Classification-2011-12 (Accessed July 16 2014).

Seresinhe, C. I., Moat, H. S. & Preis, T. (2017) Quantifying scenic areas using crowdsourced data. *Environment and Planning B: Urban Analytics and City Science*: 45 (3): 567-582.

Seresinhe, C. I., Preis, T. & Moat, H. S. (2015) Quantifying the impact of scenic environments on health. *Scientific Reports*, 5: 16899.

Seresinhe, C. I., Preis, T. & Moat, H. S. (2016) Quantifying the link between art and property prices in urban neighbourhoods. *Royal Society Open Science*, 3 (4): 160146.

Seresinhe, C. I., Preis, T. and Moat, H. S. (2017) Using deep learning to quantify the beauty of outdoor places. *Royal Society Open Science*: 4 (7): 170170.

Sharif Razavian, A., Azizpour, H., Sullivan, J. & Carlsson, S. (2014) CNN features off-the-shelf: an astounding baseline for recognition. In: *IEEE conference on computer vision and pattern recognition, 23 - 28 Jun 2014, Columbus, Ohio*. IEEE: pp. 806-813.

Sheets, V. L. & Manzer, C. D. (1991) Affect, cognition, and urban vegetation: Some effects of adding trees along city streets. *Environment and Behavior*, 23 (3): 285-304.

Shiffman, S., Stone, A. A. & Hufford, M. R. (2008) Ecological momentary assessment. *Annual Review of Clinical Psychology*, 4 (1): 1-32.

Simonyan, K. & Zisserman, A. (2014) Very deep convolutional networks for large-scale image recognition. In: *International Conference on Learning Representations, 14 - 16 April 2014, Banff, Canada*.

Stadler, B., Purves, R. & Tomko, M. (2011) Exploring the relationship between land cover and subjective evaluation of scenic beauty through user generated content. In: *25th International Cartographic Conference, 3 - 8 July 2011, Paris, France*.

Stamps, A. E. (2002) Fractals, skylines, nature and beauty. *Landscape and Urban Planning*, 60 (3): 163-184.

Stutzer, A. & Frey, B. S. (2008) Stress that doesn't pay: The commuting paradox. *The Scandinavian Journal of Economics*, 110 (2): 339-366.

Sugiyama, T., Francis, J., Middleton, N. J., Owen, N. & Giles-Corti, B. (2010) Associations between recreational walking and attractiveness, size, and proximity of neighborhood open spaces. *American Journal of Public Health*, 100 (9): 1752-1757.

Suh, E., Diener, E. & Fujita, F. (1996) Events and subjective well-being: Only recent events matter. *Journal of Personality and Social Psychology*, 70 (5): 1091-1102.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. & Rabinovich, A. (2015) Going deeper with convolutions. In: *IEEE Conference on Computer Vision and Pattern Recognition, 7 - 12 June 2015, Boston, Massachusetts*. IEEE: pp. 1-9.

Taigman, Y., Yang, M., Ranzato, M. & Wolf, L. (2014) DeepFace: Closing the gap to human-level performance in face verification. In: *IEEE conference on computer vision and pattern recognition, 23 - 28 June 2014, Columbus, Ohio*. IEEE: pp. 1701-1708.

Tan, Y., Tang, P., Zhou, Y., Luo, W., Kang, Y. & Li, G. (2017) Photograph aesthetical evaluation and classification with deep convolutional neural networks. *Neurocomputing*, 228: 165-175.

Tenerelli, P., Demšar, U. & Luque, S. (2016) Crowdsourcing indicators for cultural ecosystem services: A geographically weighted approach for mountain landscapes. *Ecological Indicators*, 64 (1): 237-248.

Tennessen, C. M. & Cimprich, B. (1995) Views to nature: Effects on attention. *Journal of Environmental Psychology*, 15 (1): 77-85.

(2000) *The geography of cool*. [online] Available from: https://www.economist.com/moreover/2000/04/13/the-geography-of-cool (Accessed 5 May 2015).

Thompson, C. W., Roe, J., Aspinall, P., Mitchell, R., Clow, A. & Miller, D. (2012) More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning*, 105 (3): 221-229.

Triguero-Mas, M., Dadvand, P., Cirach, M., Martínez, D., Medina, A., Mompart, A., Basagaña, X., Gražulevičienė, R. & Nieuwenhuijsen, M. J. (2015) Natural outdoor environments and mental and physical health: Relationships and mechanisms. *Environment International*, 77: 35-41.

Ulrich, R. S. (1993) Biophilia, biophobia, and natural landscapes. In: *The biophilia hypothesis*. Washington DC: Island Press: 73-137.

Ulrich, R. S., Simons, R. F., Losito, B. D., Fiorito, E., Miles, M. A. & Zelson, M. (1991) Stress recovery during exposure to natural and urban environments. *Journal of Environmental Psychology*, 11 (3): 201-230.

Ulrich, R. S. (1979) Visual landscapes and psychological well-being. *Landscape Research*, 4 (1): 17-23.

Ulrich, R. S. (1983) Aesthetic and affective response to natural environment. In: Altman, I. & Wohlwill, J. F. (eds.) *Human Behavior and the Natural Environment*. Boston: Springer US: 85-125.

Ulrich, R. S. (1984) View through a window may influence recovery from surgery. *Science*, 224 (4647): 420-421.

University of Essex. Institute for Social and Economic Research, NatCen Social Research, Kantar Public. (2015) *Understanding Society: Waves 1-7, 2009-2016 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. [data collection]. 8th Edition.* UK Data Service. SN: 6931. http://doi.org/10.5255/UKDA-SN-6931-7

van den Berg, A. E., Maas, J., Verheij, R. A. & Groenewegen, P. P. (2010) Green space as a buffer between stressful life events and health. *Social Science & Medicine*, 70 (8): 1203-1210.

Vespignani, A. (2009) Predicting the behavior of techno-social systems. *Science*, 325 (5939): 425-428.

Wagenmakers, E.-J. & Farrell, S. (2004) AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, 11 (1): 192-196.

Watts, D. J. (2007) A twenty-first century science. *Nature*, 445 (7127): 489-489.

Wheeler, B. W., Lovell, R., Higgins, S. L., White, M. P., Alcock, I., Osborne, N. J., Husk, K., Sabel, C. E. & 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 & Place*, 18 (5): 1198-1201.

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.

White, M. P., Alcock, I., Wheeler, B. W. & Depledge, M. H. (2013a) 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., Alcock, I., Wheeler, B. W. & Depledge, M. H. (2013b) Coastal proximity, health and well-being: Results from a longitudinal panel survey. *Health & Place*, 23 (1): 97-103.

White, M. P., Pahl, S., Wheeler, B. W. & Depledge, M. H. (2017) Natural environments and subjective wellbeing: Different types of exposure are associated with different aspects of wellbeing. *Health & Place*, 45: 77-84.

Wikipedia. (2016) *Wikipedia corpus*. [online] Available from: https://dumps.wikimedia.org/enwiki/latest/ (Accessed 14 July 2016).

Wood, S. A., Guerry, A. D., Silver, J. M. & Lacayo, M. (2013) Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, 3: 2976.

Wooldridge, J. (2009) *Introductory econometrics: A modern approach. 4th edition. 4th edition.* Cincinnati, OH: South-Western College Publishing.

Lu, X., Lin, Z., Jin, H., Yang, J. & Wang, J. Z. (2015) Rating Image Aesthetics Using Deep Learning. *IEEE Transactions on Multimedia*, 17 (11): 2021-2034.

Zaltz Austwick, M., O'Brien, O., Strano, E. & Viana, M. (2013) The structure of spatial networks and communities in bicycle sharing systems. *PLOS ONE*, 8 (9): e74685.

Zhou, B., Khosla, A., Lapedriza, A., Torralba, A. & Oliva, A. (2018) Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40 (6): 1452-1464.

Zhou, B., Lapedriza, A., Xiao, J., Torralba, A. & Oliva, A. (2014) Learning deep features for scene recognition using places database. In: *Advances in Neural Information Processing Systems 27, 8 - 13 December 2014, Montreal, Canada*. New York: Curran Associates, Inc.: pp. 487-495.

Zhou, B., Liu, L., Oliva, A. & Torralba, A. (2014) Recognizing City Identity via Attribute Analysis of Geo-tagged Images Computer Vision. In: Fleet, D., Pajdla, T., Schiele, B. & Tuytelaars, T. (eds.) *Computer Vision – ECCV 2014. ECCV 2014. Lecture Notes in Computer Science*. Cham: Springer International Publishing: 519-534.

Zielstra, D. & Hochmair, H. H. (2013) Positional accuracy analysis of Flickr and Panoramio images for selected world regions. *Journal of Spatial Science*, 58 (2): 251-273.

Zou, H. & Hastie, T. (2005) Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67 (2): 301-320.

Zube, E. H. & Pitt, D. G. (1981) Cross-cultural perceptions of scenic and heritage landscapes. *Landscape Planning*, 8 (1): 69-87.

Zube, E. H., Pitt, D. G. & Evans, G. W. (1983) A lifespan developmental study of landscape assessment. *Journal of Environmental Psychology*, 3 (2): 115-128.