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Happiness is greater in natural environments

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ABSTRACT

Links between wellbeing and environmental factors are of growing interest in psychology, health, conservation, economics, and more widely. There is limited evidence that green or natural environments are positive for physical and mental health and wellbeing. We present a new and unique primary research study exploring the relationship between momentary subjective wellbeing (SWB) and individuals' immediate environment within the UK. We developed and applied an innovative data collection tool: a smartphone app that signals participants at random moments, presenting a brief questionnaire while using satellite positioning (GPS) to determine geographical coordinates. We used this to collect over one million responses from more than 20,000 participants. Associating GPS response locations with objective spatial data, we estimate a model relating land cover to SWB using only the within-individual variation, while controlling for weather, daylight, activity, companionship, location type, time, day, and any response trend. On average, study participants are significantly and substantially happier outdoors in all green or natural habitat types than they are in urban environments. These findings are robust to a number of alternative models and model specifications. This study provides a new line of evidence on links between nature and wellbeing, strengthening existing evidence of a positive relationship between SWB and exposure to green or natural environments in daily life. Our results have informed the UK National Ecosystem Assessment (NEA), and the novel geo-located experience sampling methodology we describe has great potential to provide new insights in a range of areas of interest to policymakers.

1. Introduction

1.1. Pathways

There are at least three reasons for thinking that experiences of natural environments will be positively related to health, wellbeing and happiness. First, there appear to be direct pathways by which such experiences affect the nervous system, bringing about stress reduction and restoration of attention. The existence of such pathways – *biophilia* – has plausible evolutionary explanations: an innate human emotional affiliation to nature and living organisms in general is proposed as an adaptation to our reliance on the natural environment throughout all but the past 10,000 years of our history (Wilson, 1993). Affinities with more specific habitats, including savanna and forest, have similarly been postulated on the basis that these habitats would have provided our hominin ancestors with the greatest reproductive success (Falk and Balling, 2010; Han, 2007).

Second, natural environments may be lower in environmental 'bads' that have significant negative impacts on physical and mental wellbeing, which in turn could affect happiness. Adverse health effects of noise and air pollution are well documented. Chronic traffic noise exposure in urban environments can cause severe sleep disturbance, hearing impairment, tinnitus, and raised stress levels, leading to high blood pressure, coronary heart disease, stroke, and possibly immune system and birth defects (Passchier-Vermeer and Passchier, 2000). Similarly, air pollution can lead to a wide range of respiratory and cardiovascular problems (Gouveia and Maisonet, 2005). As noted by Welsch (2006), this link does not require that individuals are conscious of the causal relationship between an environmental problem and their own happiness. However, awareness of a local environmental problem, and of its negative effects on human and ecosystem health, could also act to reduce happiness levels directly and

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independently. There is evidence that individuals' perceptions of air pollution are positively correlated with objective pollution measures (Day, 2007). This makes individuals' perceptions of air pollution an additional route by which the pollution may influence their happiness.

Third, natural environments might increase happiness by facilitating and encouraging – for practical, cultural and/or psychological reasons – behaviours that are physically and mentally beneficial, including physical exercise, recreation and social interaction (Barton and Pretty, 2010a; Morris, 2003).

1.2. Evidence

Researchers have pursued both observational and experimental evidence on the links between physical or mental wellbeing and the natural environment. Observational studies have related averaged wellbeing measures to aggregate environmental characteristics between geographical regions (e.g. Mitchell and Popham, 2007, 2008; Vemuri and Costanza, 2006; Engelbrecht, 2009). They have also compared individuals' SWB reports or medical records with the proximity of their homes to natural environments, or with alternative indicators of local environmental quality (e.g. de Vries et al., 2003; Kaplan, 2001; Brereton et al., 2008; Rehdanz and Maddison, 2008; Maas et al., 2009). Experimental and quasi-experimental studies have investigated physiological and psychological effects of exposure to images of different environment types (e.g. Berto, 2005; White et al., 2010) or to short-term interventions bringing subjects into contact with nature (e.g. Ryan et al., 2010; Hartig et al., 2003; Barton and Pretty, 2010b). They have also related health outcomes or frequency of healthcare-seeking behaviour to views of nature in controlled institutional settings (e.g. Ulrich, 1984; Moore, 1981).

Most such studies report beneficial impacts of natural environments on health or wellbeing, but they have some common weaknesses. Observational studies measure domestic proximity to natural environments but not actual experiences of such environments (which may not occur near home, and may occur elsewhere); cannot provide data on the moment-by-moment hedonic or affective element of wellbeing; and are commonly reliant on retrospective assessments that are subject to substantial recall bias (Robinson and Clore, 2002). Experimental studies are stronger in these respects but, by their nature, have lesser ecological validity – that is, they tell us a limited amount about people's real experiences of natural environments in their everyday lives.

Longitudinal study designs in which participants provide ongoing reports of their everyday experience – Ecological Momentary Assessment (EMA), the Experience Sampling Method (ESM), and the Day Reconstruction Method (DRM) – provide some of the best evidence regarding influences on wellbeing in general (Shiffman et al., 2008; Hektner et al., 2007; Kahneman et al., 2004). However, these methods have conventionally been cumbersome, expensive, and limited to very small samples (Killingsworth and Gilbert, 2010). They have also been unable to provide objective location data. For these reasons, such ongoing assessment methods have not previously been applied to the study of wellbeing in different environments.

This paper aims to address some of the shortcomings of previous research and improve the understanding and measurement of the relationship between happiness and the natural environment. We explore the link between momentary, experienced subjective wellbeing and individuals' immediate environment, using a pioneering, large-scale ESM study in the UK. We focus on land cover, including green and blue space types. Unlike most previous research – based on retrospective evaluations of wellbeing and domestic proximity to an environment – our study captures individuals' momentary experiences of both.

1.3. Structure of this paper

The paper proceeds as follows. The next section locates our approach within the broader context of happiness and wellbeing research. Section 3 describes our ESM technique. Section 4 presents and discusses our results, including a variety of robustness checks. Section 5 concludes, summarizing key findings and discussing the potential for future applications.

2. Approach to happiness and wellbeing

A variety of terms are used in the cross-disciplinary literature around happiness, including happiness, (subjective) wellbeing, life satisfaction, experienced utility, and quality of life. It is common for several such terms to be used interchangeably, as synonyms, and also for the same terms to be applied to different concepts or quantities – such as the results of quite distinct survey questions – in different studies (MacKerron, 2012b).

A variety of ways to conceive of happiness and wellbeing are available too. Dolan and Metcalfe (2012) provide a useful summary, distinguishing three broad accounts: *objective lists*, in which wellbeing is the fulfilment of a fixed set of material, psychological and social needs, identified exogenously; *preference satisfaction*, the standard economic view, in which wellbeing consists in the freedom and resources to meet one's own wants and desires; and *happiness* or *subjective wellbeing* (SWB), in which wellbeing is measured by people's self-reports in response to appropriate questioning.

This third account, SWB, can be further divided into three categories: *evaluative* SWB, in which people are asked for global assessments of their lives – for example, their 'satisfaction with life as a whole'; *eudemonic* SWB, based on reports concerning 'flourishing', purpose and meaning in life, and the realization of one's potential; and *hedonic* or *experienced* SWB, based on reports of mood, affect or emotion, and representing the Benthamite, Utilitarian view of wellbeing as pleasure and pain.

As one might expect, answers across the three categories of SWB or happiness tend to be positively correlated – and also related to wellbeing according to the other two broad accounts – but they may respond differentially to different external factors, such as income (Kahneman and Deaton, 2010). The ESM method employed here provides particularly rich information on the third category – hedonic, experienced SWB.

3. Methods

3.1. Registration and experience sampling

We developed a native software application (app) named *Mappiness* for Apple iPhone, iPad and iPod devices using the Apple Software Development Kit (Apple Inc., 2010). We also developed back-end server software to communicate with the app, and a public-facing website providing information to actual and prospective respondents (http://www.mappiness.org.uk). The app is distributed via Apple's App Store, a central software repository accessible to all device users.

Participants are self-selecting and recruited opportunistically, assisted by coverage in traditional and social media. The app was highlighted in the App Store (in the Featured/New section) for two weeks shortly after launch; it has been the subject of thousands of messages on the social networking sites Facebook and Twitter; and the project has had extensive coverage on television, radio, and in the specialist and mainstream press. The app is also well adapted to spread amongst friends and acquaintances, since its beeps may interrupt social interaction and make it a subject of conversation.

Prospective participants download the *Mappiness* app at no charge, indicate their informed consent to taking part, and provide basic demographic and health-related information (the full questionnaire is reproduced in the Supplementary Material). After this registration process, they are then signalled (beeped) at random moments during their daily lives, with a frequency and during hours they choose (the defaults are twice a day between 08.00 and 22.00), and asked to report the extent to which they are feeling 'Happy' on a continuous sliding scale. Participants are also asked whom they are with, where they are, and what they are doing (the full questionnaire is again reproduced in the Supplementary Material, and example screens are shown in Figure S1 there). While they answer, precise location is determined by satellite positioning (Global Positioning System, GPS). The encrypted data is then transmitted to our server. Participants receive simple feedback, charting their happiness in different contexts, and can take part for as long or short a period as they wish.

Necessary conditions for receiving a valid response to a signal include that the signalled participant is: in possession of the powered-on signalling device; in an area with wireless data reception (e.g. not on an underground rail system); able to hear the signal (e.g. not in a noisy club); able to respond (e.g. not driving); and willing to do so. Apart from wireless data reception, these same conditions apply to all signal-contingent ESM studies. These requirements will inevitably restrict the sample of experiences captured (wireless data reception is available in the vast majority of UK locations, but is regrettably somewhat less widespread in the most rural and remote locations, which are also more likely to be natural environments).

Regarding the sample of individuals, the requirement that participants own an iPhone, and that they self-select into the study, rules out obtaining a probability sample, or even one that is representative on observable characteristics (we describe the characteristics of our sample in Section 4.1). On the other hand, use of the iPhone provides substantial advantages over traditional ESM protocols using paper diaries or handheld computers. The device is small and convenient. Since it is already owned and provides other functions to the user, it is also likely to be kept charged, switched on, and within reach without any additional burden on participants. Responses cannot be entered for any time other than the current moment (this may be a serious problem in diary-based studies, where in some cases a large proportion of responses are found to have been fabricated long before or after the signalling time: Stone and Shiffman, 2002). And the relatively low burden on respondents, and low marginal cost in researcher time and money of each additional respondent, enable a sample size orders of magnitude higher than has traditionally been achievable. A more detailed treatment of the methods outlined in this section is provided by MacKerron (2012a).

3.2. Spatial data

We associate each response with three key spatial and environmental indicators using the GPS location data: broad habitat or land cover type, weather conditions and daylight status. Our main focus is on land cover (including green and blue space types). We calculate the habitat type at each reported point location using the 25 m-resolution UK Land Cover Map 2000 (LCM) (Fuller et al., 2002), grouping LCM subclasses into the same nine broad habitat categories used in the UK NEA (UK National Ecosystem Assessment, 2011). These categories are as listed in Table 1, and their composition is provided in Table S1 in the Supplementary Material. Arguably, nearby habitats might also form part of a respondent's experience. However, since the habitat types generally occur in areas much larger than a 25×25 m square, we believe that land cover type at the respondent's point location represents a reasonable proxy for the habitat that the respondent is experiencing.

As an important control variable, we also assess weather conditions at the reported location at the time of the report. Using data from Weather Underground, which collates data from 280 weather sensors across the UK several times per day, we link each response with weather conditions reported by the station nearest the response location at the moment nearest the response timestamp. Finally, we calculate whether it was daylight at the response date, time and location using the NOAA sunrise/sunset calculations available within the *StreamMetabolism* library of the *R* statistical package (Sefick, 2009; R Development Core Team, 2011).

3.3. Data scope and filtering

Our analysis is based on 1,138,481 responses from 21,947 UK participants. We believe these sample sizes to be the largest ever achieved by an ESM study. The responses cover a period of approximately six months from the app's launch in mid-August 2010 to mid-February 2011, and are validated according to three criteria. First, they must be prompted by a signal: we identify such responses as those starting within 60 min of a previously unanswered signal, and completed within a further 5 min. To ensure a fully random sample of experiences, we would ideally like all participants to respond instantaneously to all signals. Since this is not realistic, varying judgments have been made in previous research regarding the maximum acceptable response delay. Our 60 min cut-off is relatively generous in relation to the EMA literature: Stone and Shiffman (2002, p. 239), for example, "would be uncomfortable with delays of 30 min or more". To ensure robustness of our findings, we therefore ran alternative analyses with a 20 min maximum delay. As noted below, this altered delay criterion did not qualitatively change our results.

Second, responses must have a UK GPS location for which, if outdoors, the device-reported accuracy is ± 250 m or better. Third, local weather data must be available for within 3 h of the response time. In an ideal world, we would like to know the geographical coordinates of each outdoor response with absolute precision, and we would like to know the weather conditions at that location at the precise moment of responding. In practice we must make a trade-off between accuracy and exclusion rate. Our choice to exclude outdoor responses with a reported accuracy worse than ± 250 m has a very modest effect on sample size (excluding less than 0.25%, or just over 4500 responses). To check robustness, we ran alternative analyses in which results were excluded if reported accuracy was worse than ± 100 m. As noted below, this produced no qualitative change in our results. We accept the nearest weather station location in all cases – the distance is always less than 60 km – and exclude responses only in the very rare case that complete weather data was not reported by that station within 3 h of (before or after) the response.

Descriptive statistics and econometric analyses are reported for these valid responses and their contributing participants only.

3.4. Econometric model

The study data represent a very large, unbalanced panel, with large N (the number of individuals) and highly variable T (the number of assessments per individual). We use the data to estimate a fixed effects or within estimator model, explaining the relationship of habitat type and other environmental variables to

Table 1
Descriptive statistics for explanatory variables. All variables are 0/1 dummies. All percentages – including where variables are interacted with the variable 'Outdoors' – are calculated in relation to the full sample of 1,138,481 responses.

Variable	%	Count	Variable	%	Count
Participant is...			*Selected activities*		
Indoors	85.41	972,398	Walking, hiking	1.22	13,847
In a vehicle	7.11	80,981	Sports, running, exercise	1.02	11,653
Outdoors	7.48	85,102	Gardening, allotment	0.20	2305
			Bird watching, nature watching	0.06	695
Land cover type when participant is outdoors			Hunting, fishing	0.03	293
Marine and coastal margins	0.06	735			
Freshwater, wetlands and flood plains	0.06	668	*Participant is with...*		
Mountains, moors and heathland	0.04	410	Spouse, partner, girl/boyfriend	24.34	277,073
Semi-natural grasslands	0.34	3910	Children	10.68	121,555
Enclosed farmland	0.81	9235	Other family members	8.50	96,814
Coniferous woodland	0.04	501	Colleagues, classmates	17.98	204,697
Broad-leaved/mixed woodland	0.25	2822	Clients, customers	1.63	18,510
Inland bare ground	0.14	1630	Friends	9.63	109,627
Suburban/rural developed	1.94	22,119	Other people participant knows	1.64	18,624
Continuous urban	3.78	43,072	Nobody (or strangers only)	40.42	460,158
Weather when participant is outdoors			*Participant is...*		
Daylight	6.06	69,015	At home	50.97	580,269
Sun	0.91	10,321	At work	24.53	279,242
Rain	0.65	7441	Elsewhere	24.50	278,970
Snow	0.05	589			
Fog	0.11	1236			
<0 °C	0.19	2193			
0 to <8 °C	1.15	13,130			
8 to <16 °C	2.90	32,961			
16 to <24 °C	3.22	36,636			
24+ °C	0.02	182			
0 to <5 km/h windspeed	1.06	12,064			
5 to <15 km/h windspeed	3.02	34,378			
15 to <25 km/h windspeed	2.52	28,746			
25+ km/h windspeed	0.87	9914			

happiness self-ratings. Specifically, we model the reported happiness r of individual i at location l and time t as:

$$r_{ilt} = \alpha_i + \beta_{\mathrm{p}}'\mathbf{p}_{ilt} + \beta_{\mathrm{q}}'\mathbf{q}_{ilt} + \varepsilon_{ilt}$$

where α is an individual-specific constant or fixed effect, $\mathbf{p}$ is a vector of contextual factors such as companionship and activity, $\mathbf{q}$ is a vector of local amenities and environmental conditions (which may vary through time), and ε is an error term. This model has participant-specific intercepts – the fixed effects – and is equivalent to an OLS regression in which a dummy variable is included for each participant. The fixed effects control for all time-invariant individual-specific characteristics, including personality characteristics and demographic variables such as age and income (e.g. Wooldridge, 2009). We are therefore able to estimate the influence of the natural environment on self-reported happiness using only variation between reports from the same individuals.

On the left hand side of our model, the happiness self-rating is scaled from 0 ('not at all') to 100 ('extremely'). On the right hand side we include dummies for habitat types when outdoors, which are the focus of this research. However, experience of different environments may well be associated with other variables that are important to wellbeing. For example, visits to parks could be correlated with the presence of family and friends, leisure activities, weekends, and good weather. We therefore include as control variables the indicators of daylight and weather conditions when outdoors, activity, companionship, location type, and time of day (separately for Monday – Friday and Saturday – Sunday). We also include response sequence indicators, capturing the number of previous responses by the same participant, to control for possible trends in happiness (or response behaviour) over time.

We cannot include in our model any time-invariant individual-level influences on reported happiness, such as personality characteristics or gender, since all such influences are swept up by the individual-level fixed effects. However, the estimator allows for arbitrary correlation between any individual effects (including unobserved effects) and the observed explanatory variables. This is an important property, since such correlations seem likely to exist in our data. For example, personality characteristics may very plausibly be associated with the companionship, activity and environment that a person can and does choose at any moment in time.

Basic, pooled OLS fixed effects estimation requires that the errors are homoskedastic and not serially correlated (Wooldridge, 2009). The serial correlation restriction is likely to be problematic for our data, since it seems highly plausible that unobserved influences on a person's happiness may persist from one response to the next. Therefore standard errors are calculated using the cluster-robust sandwich estimator (StataCorp, 2009), which is robust in the face of heteroskedasticity and serial correlation of the errors (Stock and Watson, 2008).

4. Results and discussion

4.1. Descriptive statistics

Our reliance on participants with iPhones clearly restricts the sample's demographic profile. Participants are relatively wealthy: median household income is approximately GBP £ 48,000, almost twice the UK median (House of Commons, 2006). They are also relatively young: 66% are aged under 35, and 95% under 50, compared to 29% and 56% respectively in the UK adult population (Office for National Statistics, 2010). 78% of participants are in employment and 13% are in full-time education. These groups are over-represented relative to the UK adult population, in which the proportions are respectively 57% and 4%, primarily at the expense of retired people, who constitute 0.5% of participants but 22% of the population (National Centre for Social Research, 2009). Participants' sex ratio is nearly balanced, however, at 55% male, compared to 49% in the UK adult population (Office for National Statistics, 2010).

The number of responses per participant ranges from 1 to 737 (mean 51.9). 14% of participants were still actively responding when the data set was extracted, so this parameter is not the same as participants' final response count. Responses come from across the UK but are concentrated around population centres, as shown in Fig. 1. In total, amongst participants who contributed at least one valid response, 48% of signals resulted in a valid response.

All explanatory variables in our analysis are 0/1 dummies, and all land cover type and weather variables are interacted with being outdoors. Note that we consider land cover, weather conditions and countryside designation status *only* as interactions with being outdoors. Although it is possible that these variables are also associated with happiness when participants are indoors or in a vehicle, the same direct link from environmental exposure to mood cannot be posited with confidence in these cases. In addition, when participants are not outdoors their location is less accurately determined by GPS, making these joined spatial data less reliable.

The variables are summarized in Table 1. The happiness response, scaled 0–100, has a mean of 66.4 and standard deviation of 21.6: as is typical for SWB parameters, its distribution is negatively skewed. The distribution, which is illustrated in Fig. 2, also shows two artefacts of the response process: spikes at the absolute extremes of the distribution, where the response slider is moved to its limit, and small troughs on either side of the midpoint, where the response slider is most commonly either left in its initial position or moved a minimum distance to the left or right. As described further below, we check robustness using a model that accounts for the spikes at the extremes as representing a consequence of response scale truncation.

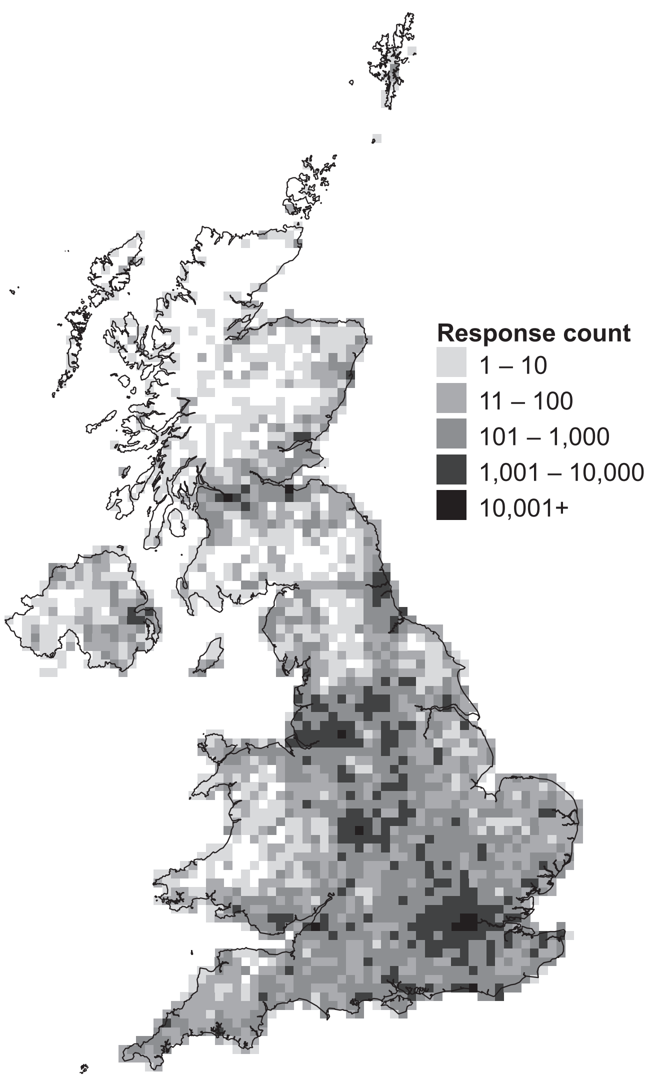

Fig. 1. Response coverage, shown as response count per 10 km cell and shaded logarithmically. Outline represents UK. This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown and the Post Office. Source for N. Ireland boundary: 2001 Census, Output Area Boundaries. Crown copyright 2003. Crown copyright material is reproduced with the permission of the Controller of HMSO.

4.2. Fixed effects model

Table 2 presents the model. All control variables show relationships with the happiness score that are intuitive and (where applicable) in line with previous research. For example, participants are happier at home than at work, and greater happiness is also associated with higher temperatures and lower wind speeds, with sunshine, and with the absence of rain and fog. Physical activities, and activities expected to be common in natural environments (such as running, gardening or birdwatching), also show substantial positive associations with happiness. Participants are happier outdoors than indoors or in a vehicle.

When outdoors, every habitat type except inland bare ground is associated with significantly higher happiness levels than the continuous urban type. Marine and coastal margins are by some distance the happiest locations, with responses approximately 6 points higher than continuous urban environments on the 0–100 scale. Alternatively expressed, this is a difference of 0.28 standard deviations, or one of similar magnitude to, for instance, the difference between attending an exhibition and doing housework.

All other green or natural environment types – 'mountains, moors, and heathlands', 'freshwater, wetlands and flood plains', woodland, grasslands, and farmland – are between 2.7 and 1.8 points happier than continuous urban environments. Suburban or rural developed environments are a little under one point happier.

As noted earlier, we cannot include in our model any time-invariant individual-level influences on reported happiness, such as gender or age, since all such influences are soaked up by the individual-level fixed effects. However, it is possible to include interactions between time-invariant individual characteristics and environmental variables, so as to explore the existence of – for example – gender or age effects. To check this, we ran an additional fixed effects model (not shown) adding in both gender and age interactions with the land cover variables. We had no prior

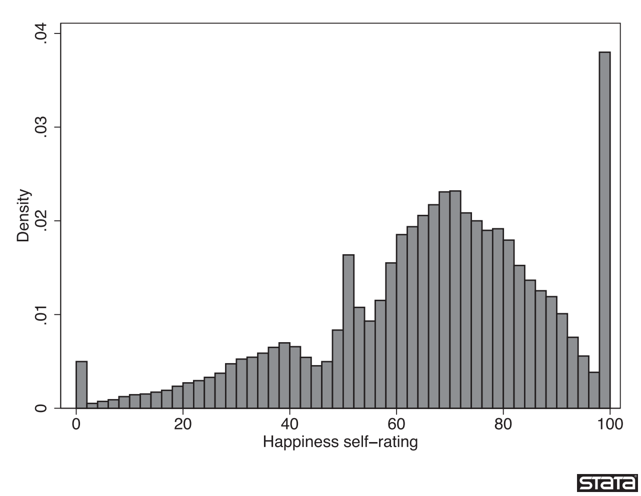

Fig. 2. Distribution of happiness self-ratings.

Table 2
Estimated model parameters. Dependent variable: reported happiness, scaled 0–100. Model: fixed effects, with participants as the groups. Standard errors are sandwich estimators clustered at participant level.

Variable	Coeff.	Std. err.	Variable	Coeff.	Std. err.
Participant is...			*Selected activities*		
Indoors (base category)	–		Sports, running, exercise	6.51***	(0.19)
In a vehicle	−0.17	(0.14)	Birdwatching, nature watching	4.32***	(0.62)
Outdoors	2.32***	(0.45)	Gardening, allotment	3.55***	(0.44)
			Hunting, fishing	3.28*	(1.36)
Land cover type when participant is outdoors			Walking, hiking	2.55***	(0.18)
Continuous urban (base category)	–		+ 36 further activity dummies	Yes	
Marine and coastal margins	6.02***	(0.68)			
Mountains, moors and heathland	2.71**	(0.87)	*Companionship*		
Woodland	2.12***	(0.34)	Spouse, partner, girl/boyfriend	4.51***	(0.11)
Semi-natural grasslands	2.04***	(0.35)	Friends	4.38***	(0.09)
Enclosed farmland	2.03***	(0.24)	Other family members	0.75***	(0.10)
Freshwater, wetlands and flood plains	1.80**	(0.63)	Clients, customers	0.43	(0.41)
Suburban/rural developed	0.88***	(0.16)	Children	0.27	(0.15)
Inland bare ground	0.37	(0.47)	Colleagues, classmates	−0.29*	(0.13)
			Other people participant knows	−0.83***	(0.19)
Weather when participant is outdoors					
Daylight	−0.11	(0.17)	*Participant is...*		
Snow	1.02	(0.72)	At home (base category)	–	
Sun	0.46*	(0.18)	At work	−2.59***	(0.12)
Fog	−1.35*	(0.54)	Elsewhere	1.73***	(0.09)
Rain	−1.37***	(0.22)			
<0 °C (base category)	–		Hour of weekday/weekend dummies (3-h blocks)	Yes	
0 to <8 °C	−0.51	(0.41)	Sequence dummies (participant's response 1, 2–11, 12–51)	Yes	
8 to <16 °C	0.29	(0.42)			
16 to <24 °C	0.99*	(0.42)	Participant-level fixed effects	Yes	
24+ °C	5.13***	(1.21)	Constant (mean fixed effect)	60.70***	(0.14)
0 to <5 km/h windspeed (base category)	–				
5 to <15 km/h windspeed	−0.20	(0.19)	Observations	1,138,481	
15 to <25 km/h windspeed	−0.52**	(0.20)	Groups (participants)	21,947	
25+ km/h windspeed	−0.94***	(0.25)	R^2 (within groups)	13.5%	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

expectations regarding the link between people's momentary experience of the surrounding environment and gender or age. We find that marine and coastal margins, woodland and farmland all have a significantly larger positive impact on women's self-reported wellbeing than men's. We also find that being outdoors has a significantly larger positive effect on older people, and that only older people are happier in mountainous regions. Further research might usefully investigate why these differences occur. Other land cover effects do not differ significantly by gender or age.

4.3. Scenarios

Certain activities, such as gardening, birdwatching, hunting and fishing, may be mainly or exclusively carried on outdoors and in natural environments. And, of course, people may be more likely to spend time in natural environments in pleasant weather. Assuming, of course, that our model is correctly specified in its inclusion of these variables as independent effects, we may simply add coefficients together to predict happiness levels in specific scenarios. Thus, for example, the predicted happiness of a person who is outdoors (+2.32), birdwatching (+4.32) with friends (+4.38), in heathland (+2.71), on a hot (+5.13) and sunny (+0.46) Sunday early afternoon (+4.30) is approximately 26 scale points (or 1.2 standard deviations) higher than that of someone who is commuting (−2.03), on his or her own, in a city, in a vehicle, on a cold, grey, early weekday morning. Equivalently, this is a difference of about the same size as between being ill in bed (−19.65) vs doing physical exercise (+6.51), keeping all other factors the same.

4.4. Robustness checks

We have performed a number of robustness checks on these results.

As an alternative approach to identifying high-quality natural environments, we re-ran the model replacing the LCM habitat variables with three (in some cases overlapping) indicators of UK landscape designations, interacted with being outdoors. The designated areas were: Areas of Outstanding Natural Beauty (AONB – including the Scottish equivalent, National Scenic Areas), with 2462 outdoor responses; National Parks (NP), with 1402 outdoor responses; and National Nature Reserves (NNR), with 117 outdoor responses. All three designations were positively and significantly related to happiness ratings (AONB coeff. 2.39, std. err. 0.55, $p < 0.0001$; NP coeff. 4.59, std. err. 0.58, $p < 0.0001$; NNR coeff. 5.00, std. err. 1.62, $p = 0.0020$).

We tested the effect of imposing more stringent response validity criteria, requiring responses to be made within 20 min of a signal instead of 60 min, and reported accuracy to be 100 m or better instead of 250 m. These criteria reduce the response sample size by just under half. The sign and significance of all LCM habitat variable coefficients are unchanged in this regression relative to that reported in Table 2, and no coefficient varies by more than 0.5 between the two.

In order to attract and motivate prospective participants to sign up to the study, and to keep them engaged in taking part, we provided some feedback about their responses – that is, some basic information about their reported happiness. We expect the value of this feedback to increase with the degree of participation. We were careful not to feed back information about environmental effects on happiness, since this was the key relationship we wished to test. However, taking part in the study for long periods of time could conceivably lead to increased reflection on states of mind, and awareness of the factors that affect these, enabling participants to act to improve their mood. To test whether giving feedback to participants over a prolonged period might have affected responses in such a way as to alter our findings, we ran a separate fixed effects model using each individual's first ten responses only. The pattern of results is broadly similar to that in Table 2, providing no compelling evidence of information feedback effects.

It is also conceivable that current mood might have an effect on the likelihood of responding to the *Mappiness* app when prompted. Or, perhaps more likely, it may be that participants initially respond to signals assiduously and irrespective of mood, but in later stages are more inclined to respond when feeling good (we have received correspondence from participants supporting this latter possibility). These hypothesis have so far proven difficult to test with our data. However, the model we ran based on the first ten responses only would suggest that, if later stage selection effects do exist, they do not affect the links we find between mood and environment.

We ran an interval regression model accounting for the truncation of happiness ratings at either extreme of the scale (10,582 responses at zero and 80,994 at 100), seen as the spikes in Fig. 2. We do not use this as our main model because fixed effects cannot be included. However, in this model all natural land cover coefficients are slightly increased in magnitude, and all remain highly significant.

As an additional test we focused on a specific activity, modelling participants' happiness when undertaking that activity in natural vs urban areas. We used the activity labelled 'Sports, running, exercise', which is undertaken in areas of both kinds. In order to investigate possible differences in self-reported happiness between people exercising in urban areas and other habitats, we re-ran our fixed effects model using only the sub-sample of reports listing this amongst current activities (11,653 reports from 5085 individuals). Our results indicate that the same people are happier when they are exercising in 'semi-natural grasslands' than when they are doing so in an urban environment. The other habitat types do not have a significant relationship with happiness in this case, but this may well be a consequence of the very much reduced sample size.

Though we include a wide range of control variables in our happiness model, we do not ask whether participants are on holiday. If participants are more likely to visit remote, high-EQ environments when on holiday, then it is possible that happiness effects we have attributed to natural environments are actually due, in whole or in part, to enjoyment of such leisure time. To help address this issue we re-estimated the model using only responses received on weekends and public holidays, when the great majority of respondents are 'on vacation' in the sense that they are presumably free to engage in leisure activities. This restriction reduces the response sample size by about two-thirds. All LCM type coefficients remain positive. Coefficients on all green and blue space types are reduced somewhat in magnitude, however, and those on the 'mountains, moors, and heathlands' and 'freshwater, wetlands, and floodplains' types are no longer significantly different from zero at the 5% level.

Finally, meaningful hypothesis testing requires that the significance level be a decreasing function of sample size (Leamer, 1978), and our sample size is very large. In addition, in interpreting our coefficients of interest, we are making multiple comparisons. We can account for the first issue by using the natural log of the sample size as a higher-than-usual critical F value when testing whether each coefficient is different from zero (Deaton, 1997). We can account for the second using the Bonferroni correction, dividing the significance threshold ($p < 0.05$) by the number of tests (Abdi, 2007). Coefficients on all green or natural land cover types except two – again, the mountain and freshwater environment types – retain significance even using the substantially more stringent thresholds calculated using these procedures.

5. Conclusions

5.1. Main results

This study provides a new line of evidence on the links between nature and subjective wellbeing. Amongst study participants, happiness is greater in natural environments, even after controlling for a wide range of potential confounders.

The relationships we estimate are highly statistically significant, and their magnitudes are substantial. We know that the relationships are not confounded at the participant level (that is, by associations between types of locations and types of people), because our model is estimated exclusively from within-individual variation. And we have controlled for a reasonably comprehensive set of potential confounders at the response level.

5.2. Limitations

Causal pathways may run in both directions, such that people choose an environment partly according to their mood (for example, individuals who already feel unhappy may be less likely to leave the home to engage in physical activity or experience natural habitats), and people's moods are partly determined by their environment. It seems plausible that the latter pathway makes an important contribution to the relationship, and future research using these data will address this in greater detail.

Our sample is limited to iPhone users who encounter the opportunity to participate in the study, and who then self-select. We did not expect to obtain a sample that is representative of the population as a whole, and indeed we did not obtain one. Caution is thus required in making any claims as to the general applicability of our results. On the one hand, we do not know of any evidence that the demographic peculiarities of our sample – who are younger, richer, and more likely to be in education or employment than average – should affect relationships between their happiness and natural environments. On the other hand, we can speculate on possible effects in both directions. For example, it might be that the base category urban environments frequented by our respondents are, in fact, nicer than the average, which could lead to an under-estimation of the positive links with other land cover types. Conversely, it could be that natural environments provide a particularly strong and enjoyable contrast with the stressful working lives of young professionals, who are over-represented in our sample, leading to an over-estimation of those same links.

Self-selection might affect the generality our findings if there were meaningful differentials in individuals' sensitivity to the environmental characteristics we examine, and if these differentials played a part in individuals' decisions to participate in the study. We do not know whether or to what extent this may be the case.

5.3. Policy

These results have informed the UK NEA (Pretty et al., 2011), and there is great potential for further developing *Mappiness*, or similar tools, for use in a wide range of environmental and policy applications.

They could be used to measure the effects of environmental interventions – such as the creation of a new woodland, clean-up of a contaminated site, introduction of a community conservation programme, or start of a green exercise programme – on momentary wellbeing. They could be used to investigate how persistent such effects are over time, and whether these interventions are more beneficial in certain geographical surroundings: for example, measuring the differential impact on subjective well-being from establishing a new woodland in a rural location, close to a city, near a deprived area, and so on. Moreover, with some straightforward modifications, similar tools could be developed specifically to monitor other aspects of wellbeing, including mental health, evaluative and eudemonic measures.

Similarly, tools like ours could be used to quantify and assess the impacts on wellbeing of environmental hazards or disasters, such as oil spills, forest fires, epidemics (e.g. foot-and-mouth disease), water or soil contamination incidents, and floods. Future versions of *Mappiness* could be developed to investigate human resilience in relation to external stresses arising from environmental change – in other words, the ability of a person or community to withstand, respond and recover from external unfavourable shocks, as well as the capacity to self-organise and adapt to emerging circumstances (Adger, 2000, 2006; Folke, 2006). This could allow us to measure day-to-day fluctuations in wellbeing and relate these to adversity or stresses in life and to a person's resilience.

Finally, there is also great potential for using these tools to enhance citizen science projects in which scientific measurements are carried out by volunteer members of local communities, with the aim of developing an evidence base – that may then inform action – regarding environmental problems in their area. *Mappiness* is a form of participatory sensing, a developing area of citizen science in which the capabilities of participants' mobile devices are used to sense the environment (Haklay, 2012). A particularly promising application here lies in combining behavioural and wellbeing information collected in this way with emerging locally-based natural resource monitoring efforts in developing countries (Fry, 2011). With the aid of mobile devices equipped with GPS, tools for ecological measurement, and *Mappiness*, local populations could collect real-time information on ecological change (such as resource damage from logging, poaching, water pollution, reef destruction or bushmeat hunting) – as is currently being trialled across many parts of the globe – whilst simultaneously measuring the associated wellbeing, health and behavioural changes. The precise way in which wellbeing would be conceptualized and measured using this method could be decided collaboratively with the local population, ensuring it would be meaningful and appropriate to context. Participatory sensing tools of this kind could also be adapted to allow engagement with non-literate people.

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Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gloenvcha.2013.03.010.

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