Access to natural greenspace and mental wellbeing: a spatial analysis

Abstract

Exposure to nature is thought to benefit mental health and wellbeing. However, many studies consider greenspace as a single entity, which overlooks the potential significance of the various forms of greenspace, and natural greenspaces in particular. This study was designed to investigate the association between different types of greenspace and mental wellbeing. Drawing wellbeing and socioeconomic data from the Annual Population Survey (2012-2015), and shapefiles from the Greenspace Information for Greater London group, the amount of greenspace accessible within a 300m walk of individual's postcodes was calculated, and categorised according to type. Spatial Error Models were used to account for spatial patterns in the data. Natural greenspace was significantly associated with improved life satisfaction (B = 0.028, p < 0.001) and happiness (B = 0.023, p = 0.019) scores. The spatial autoregressive parameter (λ) was small but significant (p < 0.001), implying slight second-order spatial variation in the model. These results imply that natural areas may be more important for hedonic mental wellbeing than other greenspaces. Future research is needed on exploring causal relationships between exposure to greenspace and mental wellbeing outcomes.

Keywords

Greenspace, built environment, GIS, urban planning

1 Introduction

While interest in healthy urban planning is growing, evidence is emerging that exposure to greenspace, and nature in particular, may have salutogenic effects on mental health and wellbeing (World Health Organisation, 2016). The UN's Sustainable Development Goals recommend "universal access to safe, inclusive and accessible, green and public spaces" for achieving sustainable cities and communities, by 2030 (Goal 11) (United Nations General Assembly, 2015).

Nature may promote positive feelings and restoration, a process conceptualised through a number of theories. Biophilia theory suggests an evolutionary advantage to spending time in nature, which historically offered shelter and sustenance, thereby attracting modern humans to natural spaces (Wilson, 1984). Attention Restoration Theory proposes that effortful, directed attention is required to undertake everyday tasks, while nature is inherently fascinating, providing an opportunity to mentally reset (Kaplan, 1984). By contrast, urban environments are less restorative, because directed attention is required to process high levels of information (Hartig et al., 2003). The Stress Recovery Theory suggests that views of nature help stressed individuals return to a relaxed emotional state (Ulrich, 1986); these theories have been validated by a number of studies (Hartig et al., 2003; Ulrich, 1984; Van den Berg et al., 2010). Therefore, much early evidence on greenspace benefits for health focuses specifically on nature, while the terms 'nature' and 'greenspace' are commonly used interchangeably (Hartig et al., 2014).

Studies have demonstrated potential mental health benefits of living in a greener neighbourhood, such as reduced mental distress (Alcock et al., 2014; Sarkar et al., 2018), and improved satisfaction (Houlden et al., 2019; White et al., 2013). However, while greenspace may be defined as any area of grass, trees, or other vegetation, it is not restricted only to more 'natural' areas (processes and features of non-human origin), but includes a broad range of features, including gardens, sports pitches, and common land. While urban greenspace takes many forms, the majority of existing research focuses on local quantity of greenspace (Houlden et al., 2018). Where greenspace is considered as a single entity, this gives insight into potential exposure, but does not consider which types of greenspace are most important for mental wellbeing, or provide the level of detail necessary to inform policy and practice (Boulton et al., 2018).

More than an absence of psychiatric distress, mental wellbeing is a measure of positive mental health which covers hedonic (happiness, satisfaction) and eudaimonic (purpose, fulfilment) dimensions (Ryan and Deci, 2001). Different types of greenspace may also offer different salutogenic opportunities (Ekkel and de Vries, 2017); greenspace may promote mental health by providing a location to pursue healthy activities, such as sports facilities facilitating exercise (Toftager et al., 2011), while parks may be used for socialising and other activities (Maas et al., 2009). As such, researchers have called for more detailed classification of greenspace, in order to determine whether or not there is appropriate 'dose' of greenspace exposure for different types of health benefit (Zhang et al., 2017; Klompmaker et al., 2018).

While several studies categorise greenspace in an effort to unpick this association, many use self-derived classifications (Annerstedt et al., 2012; van den Bosch et al., 2015; Weimann et al., 2015), or compare 'natural' and 'non-natural' environments (Luck et al., 2011; Vemuri et al., 2011), often without providing detailed definitions of these terms. Only one study has been found which compares different types of greenspace with both hedonic and eudaimonic wellbeing, revealing a positive association between the number of sports and natural spaces within a 1.6km Euclidean (straight-line) buffer and mental wellbeing (Wood et al., 2017); However, this study was based on a small selective sample of under 500 people living in Perth, Australia.

While there are no legal requirements for access distance to greenspace, different sectors have outlined their own recommendations. Fields in Trust calculate their Green Space Index for provision based on a 10-minute walk between residents and their nearest local greenspace, operationalised as an 800m Euclidean distance (Fields in Trust, 2018). More specifically, the Greater London Authority suggests that local parks and open spaces of 2ha should be no more than 400m from homes (Greater London Authority, 2017). The UK government's Accessible Natural Greenspace Standard specifies all individuals should have a 'natural' greenspace of at least 2ha within a 300m walk of their home, a recommendation based on pilot schemes and surveys (Natural England, 2010). Frequency of use has been shown to decline for greenspaces located further than 300m from individuals (Ekkel and de Vries, 2017), which may contribute to meeting government recommendations for physical activity (Klompmaker et al., 2018). Furthermore, greenspace within 300m shows the strongest relationship with mental wellbeing, with associations declining over greater distances (Houlden et al., 2019). However, studies of greenspace accessibility tend to use the Euclidean measure (Bjork et al., 2008; Triguero-Mas et al., 2015), whereas calculating street network distance is more accurate and provides an indication of accessibility on foot, and requires further investigation. Greenspace within a 300m network buffer was therefore chosen for this study.

To investigate the assumption that 'nature' should be provided, this research aimed to examine access to different types of urban greenspace. As there currently exists no standardised greenspace typology for use in research, the former Planning Policy Guidance provided by the UK government was used (PPG17), which provides detailed, consistent and well-defined categories for greenspace planning, although it has not as of yet been applied to research on mental wellbeing (Houlden et al., 2018).

In addition to these analytical complexities, both greenspace and individual-level data inherently vary spatially, meaning associations between people and their environment may further depend on location. People who live in greener areas may spend more time in their nearby parks (Maat and De Vries, 2006), or feel more connected to nature (Cohen-Cline et al., 2015); this connection may further encourage some individuals to reside in areas with more natural greenspace (Maat and De Vries, 2006). Additional location-specific features, such as environmental and cultural factors, may also influence this relationship (Lachowycz and Jones, 2013). In traditional models, such as linear or logistic regression, which are most common in the literature, these geospatial nuances are overlooked, which may cause errors to be underestimated (Anselin, 2001). This study therefore additionally considered the geographic structure of the data, to select analytical techniques which reflect the geospatial element of these associations and provide more robust estimates of the coefficients, as has been shown to be effective for capturing spatial variation in greenspace accessibility (Houlden et al., 2019; Wu et al., 2018)

This study tested the hypotheses that access to natural greenspace is more strongly associated with mental wellbeing than other types of greenspace.

2 Methods

2.1 Sample and setting

Individual data were drawn from the Annual Population Survey (APS) 2012-2015 Pooled Dataset (Office for National Statistics Social Survey Division, 2016), a quarterly survey of UK residents undertaken by the ONS; the original sample for the years 2012 to 2015 included 567,481 individuals, with an approximate response of 55%. Of these, approximately 165,000 respondents completed the wellbeing questionnaire. The final dataset comprised 25,079 individuals, as greenspace data availability restricted analyses to London. The survey covers mental wellbeing, socio-economic status, demographic and living conditions, alongside full postcode and LSOA (Lower Layer Super Output Areas). There are 4,844 LSOAs in London, with mean area $0.33km^2$ and population 1,700 (Greater London Authority, 2014). These administrative districts were used to link local area deprivation and population density to individual respondents.

2.2 Study variables

2.2.1 Mental wellbeing

Mental wellbeing was measured by three questions developed by the ONS (Office for National Statistics Social Survey Division, 2016) for monitoring wellbeing in the UK (Dolan et al., 2011). They ask: 'Overall, how satisfied with your life are you nowadays?' (life satisfaction), 'To what extent do you feel the things you do in your life are worthwhile?' (worth) and 'How happy did you feel yesterday?' (happiness), with responses rated on a scale of 0– 10. These questions are designed to cover hedonic (life satisfaction, happiness) and eudaimonic (worth) mental wellbeing.

2.2.2 Individual and household-level covariates

Potential confounding factors were identified from the published literature and survey questions available (White et al., 2013; Triguero-Mas et al., 2015). Variables at individual level comprised age (10-year groups), sex, marital status (married/cohabiting or otherwise), ethnicity (Census categories), and education (degree/diploma). Health was ascertained using self-reported general health (on a likert-type scale from very good to very poor). Socio-economic status was assessed by income (quintiles), economic activity (employed, unemployed or inactive) and housing tenure. Living circumstances were characterised by the individual's housing type (detached, semi-detached, terraced, flat, other) (Office for National Statistics Social Survey Division, 2016).

2.2.3 Local area characteristics

Local area data from the London Data Store provide population statistics and Indices of Multiple Deprivation (IMD) for each London LSOA (Department for Communities for Local Government, 2010). IMD scores are calculated across a number of domains including education, crime and access to services, with a higher aggregate score indicative of a more deprived LSOA. Population density was calculated for each LSOA.

2.2.4 Location and street network

The Ordnance Survey Code Point Map provides a centroid for each postcode (Ordnance Survey, 2017a). This provided spatial coordinates for each individual, and was linked with the

OS Open Roads shapefile (Ordnance Survey, 2017c), which contains a street network and can be spatially connected to the postcodes shapefile, APS and greenspace data, allowing the travel distance between individuals and greenspaces to be calculated.

2.2.5 Greenspace

Greenspace data were obtained from the Greenspace Information for Greater London group (GiGL), who collate data from London Borough councils. At the time of conducting these analyses, this was the largest and most comprehensive dataset of greenspace typology available in England, comprising GIS (Geographic Information System) shapefiles with polygons describing the shape, size and location of over 20,000 public greenspaces in London (Greenspace Information for Greater London CIC, 2017). The location allows spatial linkage to the other data files. Greenspaces larger than 2ha in size were included, to investigate the Natural England guideline that individuals should have access to a natural greenspace within 300m of their home (Natural England, 2010).

Greenspaces are assigned a category, according to the UK Government's Planning Policy Guidance (PPG17) definitions (Planning Policy Guidance, 2002), based on site surveys conducted by the Borough councils (Greenspace Information for Greater London CIC, 2017). For the purposes of this research, the categories Parks and Gardens (hereafter called parks), Natural and Semi-natural Urban Greenspaces (natural greenspace) and Outdoor Sports Facilities (sports) were directly studied; these were the most populous categories available, and enabled us test whether access to natural spaces was more strongly associated with mental wellbeing, compared to other types most commonly studied on the literature (Mitchell, 2013; Van den Berg et al., 2010; Wood et al., 2017). These are also the types which build on theories of greenspace and health (Ekkel and de Vries, 2017), with natural environments providing stress and restoration benefits (Kaplan, 1995; Ulrich, 1986), sports areas facilitating exercise (Toftager et al., 2011), and parks often used for socialising (Maas et al., 2009).

The remaining greenspaces were assigned to the 'Other' category, to be used as the reference field; this grouping included Allotments and Amenity greenspaces (which may be exclusive to certain groups), Green Corridors (which are excluded from the Fields in Trust consideration of greenspace, as they do not provide a designated useable area (Fields in Trust, 2018)), Civic Spaces (which may not be green), and other spaces such as cemeteries and urban fringe, as these were very few. Details of the classification system are provided in Supplementary Table 1. The process of combining and analysing these datasets is visualised in Supplementary Figure 1.

2.3 Analysis

Using ArcGIS (ESRI, 2011), the amount of greenspace within 300m walking distance of individual's homes was calculated. Postcodes in the APS data were spatially linked to the Code Point postcode centroids and then with roads. The ArcGIS Network Analyst extension was used to calculate distances along the street network. The whole area of each identified greenspace was retained and used to calculate the total amount of greenspace of each type which may be accessed within 300m walking distance of individuals; this is in line with other studies of greenspace access on foot (Wood et al., 2017). The process of creating a network buffer is visualised in Figure 1, with the background map obtained from OpenStreetMap (OpenStreetMap contributors, 2018).

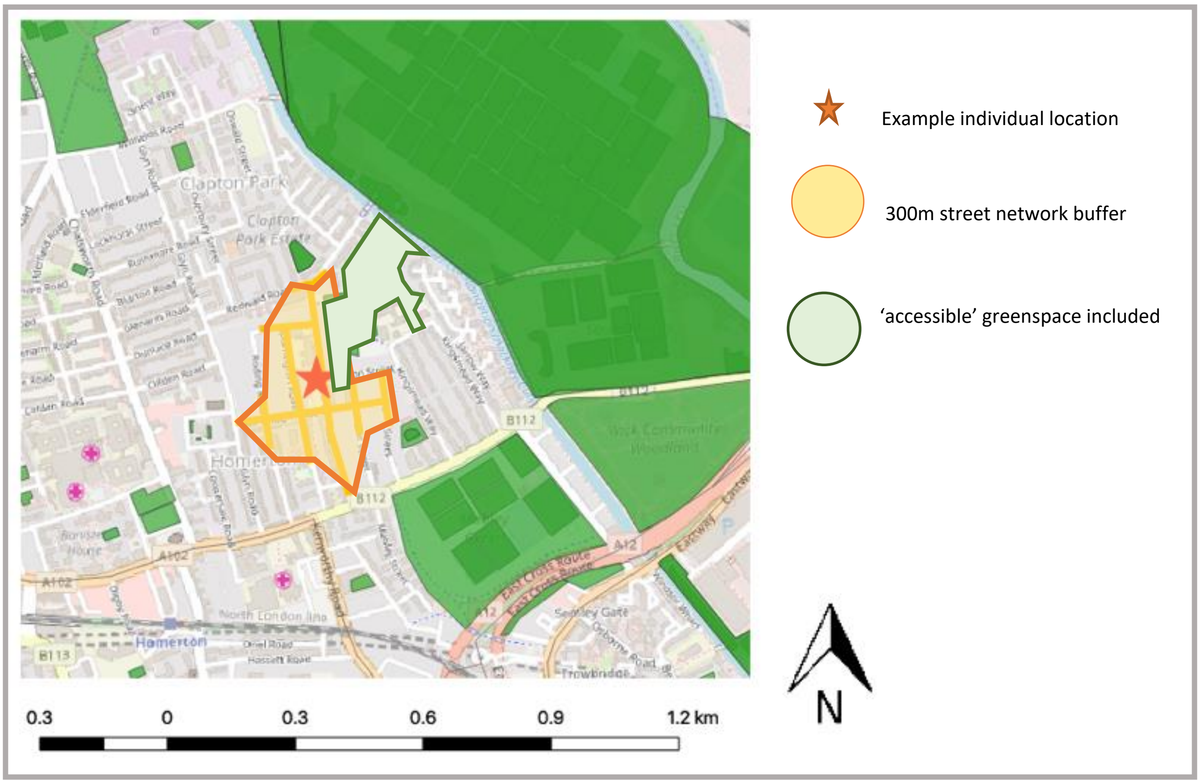

Figure 1 Calculating a 300m network buffer around an individual

R (The R Foundation for Statistical Computing, 2014) spatial and statistical packages were then used to combine all data and examine, statistically and visually, the distributions of all greenspace, wellbeing and potentially confounding variables.

Simple Ordinary Least Squares (OLS) regression models were calculated, to predict mental wellbeing scores from the amount of different types of greenspace accessible within 300m, for each wellbeing variable in turn (life satisfaction, worth, happiness), using the Other category as the reference. Tests for bivariate associations were then run, between each of the individual variables and mental wellbeing and then the amount of accessible greenspace in turn. The following were significantly associated with both, and therefore included in the models as potential confounders: age, sex, marital status, ethnicity, general health, education, employment status, income, housing tenure, housing type, LSOA population density and LSOA deprivation. Statistical tests revealed minimal evidence of multicollinearity between these factors. OLS multivariate models were then built, including all potentially confounding socioeconomic and local area variables. Baseline models, including only these factors, were calculated, so the contribution of adding greenspace indicators could be observed; including greenspace significantly improved fit.

Moran's *I* tests were used to identify any spatial autocorrelations within the data. Significant autocorrelation values imply that neighbouring individuals are more similar (or different) than would be expected by chance. This causes standard errors to be underestimated and significance to be overstated, hence such patterns must be taken into account (Haining and Haining, 2003). A *K* nearest neighbours (*KNN*) approach was implemented, using Euclidean distance between individuals' postcode centroid, to identify the closest *N* points for each individual. Taking the rounded square root of the number of instances (25,079) as *K*, 160 nearest neighbours were identified. For each model, the Global Moran's *I* statistics was used to measure spatial autocorrelation for the residual error terms; this method compares the actual residual value for each individual to a weighted matrix of neighbours, and returns a value for the overall spatial clustering of the model performance (Moran, 1950). Local Moran's *I* then provides a clustering value for each individual location, by comparing the value of each residual to that of its 160 nearest neighbours (Moran, 1950). Both measures output a value between -1 (differing values cluster) and 1 (similar values cluster), with 0 indicating no autocorrelation.

Global and local Moran's *I* was calculated for the baseline and OLS models, revealing weak but statistically significant spatial clustering, though these improved slightly as greenspace was added to the model.

Spatial Error (SE) Models, a type of Simultaneous Autoregressive models, were selected to account for slight but significant clustering of the residuals, capturing a single model for the whole sample. This technique assumes that the residuals, rather than the data variable structures, are influenced by their neighbours (Golgher and Voss, 2016). A semi-variogram plot of residuals was created to determine suitability, observing reductions in spatial dependence over distance, as the model is refined from original data and linear regression (Matheron, 1963). This was plotted for the autocorrelations within the life satisfaction variable, the OLS and SE models. This implied that residuals were spatially dependent, which may be caused by underlying random processes and hence could effectively be captured through an SE model.

In practice, the SE technique accounts for these patterns by including an autoregressive parameter, λ, in a linear model, which incorporates the spatial autocorrelation structure. This term is implemented with a spatial weights matrix, where the *K* nearest neighbours (160) of each location and the weight of each neighbour, according to proximity, are defined. The spatial dependence of a location is then modelled with a variance-covariance matrix based on the spatial weights matrix. The spatial weights matrix in SE models therefore accounts for patterns in the response variable that are not predicted by explanatory variables, but are instead related to values in neighbouring locations, due to underlying error processes.

$$MWB_i = \beta_0 + \beta_1 GS_{1i} + \cdots \beta_m x_{mi} + u_i \qquad \text{for} \qquad i = 1, \ldots, n \qquad (1)$$

$$u_i = \lambda W u + \varepsilon_i \qquad |\lambda| \leq 1 \qquad (2)$$

Equation (1) represents an SE model regression, which is identical to an OLS model except for the residual term u_i. MWB_i is the predicted value of individual *i*'s mental wellbeing score (life satisfaction, worth, happiness), β_0 is the calculated constant, β_1 is the greenspace coefficient, GS_{1i} is the amount of accessible greenspace within a 300m walk of the individual *i*'s postcode centroid and $\beta_m x_{mi}$ represents the contribution of the potentially confounding factors. The residual term u_i is then calculated, as shown in Equation (2), with the autoregressive parameter λ, which specifies the extent of the spatial autocorrelation, the weighted matrix of 160 nearest neighbours *W*, while ε_i represents the random error.

Analyses were recalculated using SE models, including each type of greenspace and using 'Other' as the reference category. Residuals were again analysed using measures of Moran's *I* and the improvements from the final model examined through the semi-variogram.

3 Results

There were 25,076 residents of London in the final sample. Mental wellbeing scores were fairly consistent for the three measures, with mean worth highest at 7.7, life satisfaction and happiness averaging 7.4 and 7.3, respectively. The mean amount of greenspace accessible within a 300m walk of individuals' homes was 5.93ha, with a reasonably high standard deviation of 6.01.

Variable	*Value*	*n*	*Mean(sd) / %*
Wellbeing	Life Satisfaction	25,076	7.4(1.81)
	Worth	25,076	7.7(1.73)
	Happiness	25,076	7.3(2.12)
Age Group	16-24	1,667	6.6
	25-34	4,979	19.9
	35-44	5,177	20.6
	45-54	4,526	18.0
	55-64	3,568	14.2
	65-74	3,012	12.0
	75+	2,147	8.6
Sex	Female	13,993	55.8
Married/Cohabiting	Yes	13,361	53.3
Ethnicity	White	16,747	66.8
	Black	2,742	10.9
	South Asian	2,686	10.7
	Other Asian	997	4.0
	Mixed	472	1.9
	Other	1,404	5.6
Diploma/Degree	Yes	10,170	40.6
General Health	Very Good	8,503	33.9
	Good	10,335	41.2
	Fair	4,652	18.6
	Poor	1,225	4.9
	Very Poor	361	1.4
Economic Activity	Employed	14,772	58.9
	Unemployed	1,245	5.0
	Inactive	9,059	36.1
Income, Quintile	1	1,988	7.92
	2	1,936	7.7
	3	2,054	8.2
	4	1,873	7.5
	5	1,958	7.8
Housing Tenure	Owns Home	6,369	25.4
Housing Type	Detached	727	2.9
	Semi-Detached	2,510	10.0
	Terraced	5,344	21.3
	Flat	7,454	29.7
	Other	50	0.3
LSOA Variables	IMD	25,076	23.4(12.48)
	Population Density	25,076	98.9(63.88)
Greenspace	Total Area (ha)	25,076	5.9(6.05)
Natural greenspace	Area	25,076	0.5(1.78)
Parks	Area	25,076	1.1(2.48)
Sports	Area	25,076	1.2(2.67)
Other greenspaces	Area	25,076	3.129(4.2446)

Table 1 Full descriptive statistics of the final sample

Results of the multivariate OLS models, shown in Table 2, predict mental wellbeing from the amount of greenspace stratified by type; these were first performed with only the three greenspace indicators (with ‘Other’ as a reference), then fully adjusted with the potentially confounding factors. In unadjusted models, a 1ha increase in natural greenspace was statistically significantly associated with an increase of 0.034 in life satisfaction ($p < 0.001$) and 0.025 in happiness ($p = 0.013$); access to sports space was positively associated with worth ($B = 0.014$, $p = 0.015$). When fully adjusted, in the life satisfaction model, including greenspace increased the R^2 value to 0.159, and revealed a positive and significant association with area of natural greenspace ($B = 0.027$, $p = 0.001$). Similar results were obtained for happiness, while increased area of parks was associated with worth ($B = 0.015$, $p = 0.015$). Global Moran’s *I* values revealed small but statistically significant positive autocorrelations in the residuals of these models; for the life satisfaction model, this was 6.320e-03 ($p < 0.001$).

Greenspace	*Life Satisfaction*			*Worth*			*Happiness*		
	B	*p*	R^2	*B*	*p*	R^2	*B*	*p*	R^2
Unadjusted Models									
Natural greenspace	***0.034***	***<0.001***	0.027	0.015	0.068	0.021	***0.025***	***0.013***	0.018
Park space	-0.001	0.926		0.005	0.415		-0.008	0.312	
Sports space	0.008	0.209		***0.014***	***0.015***		0.008	0.257	
Fully Adjusted Models									
Natural greenspace	***0.027***	***0.001***	0.159	0.011	0.151	0.098	**0.020**	**0.035**	0.092
Park space	0.007	0.109		***0.015***	***0.015***		0.005	0.521	
Sports space	0.014	0.486		0.009	0.101		-0.004	0.585	
Moran’s I	6.320e-03	<0.001		7.304e-03	<0.001		5.556e-03	<0.001	

Table 2 Results of fully adjusted OLS regression models

Local Moran’s *I* was also calculated for the residuals of each of these three models and plotted on LISA (Local Indicators of Spatial Association) maps, to visualise the locations and directions of clustering. The clusters of low and high residuals highlight where models systematically over and under-estimate the associations between greenspace and wellbeing across the study space, indicating the strength and direction of the autocorrelations. These are shown in Supplementary Figure 2a-c and demonstrate similar patterns across the results for the three wellbeing measures, with several clusters of high-high and low-low significant autocorrelations in the residuals, highlighting where the OLS models over- and under-estimate the associations between greenspace and wellbeing.

Spatial Error (SE) models were then run, to account for this spatial dependence in the structure of the residuals. These were adjusted for all potentially confounding factors. Positive and statistically significant associations were observed for the amount of natural greenspace and mental wellbeing outcomes of life satisfaction and happiness. The model predicting life satisfaction showed the strongest association, with a regression coefficient *B* of 0.028 ($p < 0.001$), which was slightly lower for happiness ($B = 0.023$, $p = 0.019$); there were no statistically significant associations for other types of greenspace, or the model predicting worth.

Wellbeing Measure	*Greenspace*	*B*	*p*	*λ*	*Likelihood Ratio*	*p*	*Moran's I*	*p*
Life Satisfaction	Natural	***0.028***	***<0.001***	0.002	55.558	<0.001	-4.748e-04	0.738
	Parks	-0.002	0.794					
	Sports	0.006	0.281					
Worth	Natural	0.010	0.196	0.002	73.081	<0.001	-4.670e-04	0.735
	Parks	0.004	0.554					
	Sports	0.010	0.071					
Happiness	Natural	***0.023***	***0.019***	0.002	43.254	<0.001	-3.563e-04	0.679
	Parks	-0.009	0.210					
	Sports	0.007	0.338					

Table 3 Results of the fully adjusted Spatial Error models

The λ coefficient was weakly positive (0.002) but statistically significant for each model (p < 0.001), implying some spatial clustering in the residuals. Aggregated results are shown in Table 3, with full results for each of these models presented in Supplementary Tables 2-4.

Examining the Global Moran's *I* values of each model revealed that SE models had effectively captured the spatial autocorrelations in the residuals. For the life satisfaction model, the *I* value was reduced to -4.748e-04, and was no longer statistically significant (p = 0.738); similar patterns were observed for the remaining models. LISA cluster plots indicating the statistical significance and direction of Local Moran's *I* for each of these associations are presented in Supplementary Figure 3a-c. There was clear reduction in the residual error local autocorrelations when compared to the linear models (Supplementary Figure 2a-c), demonstrating that the addition of greenspace and capturing of spatial processes as variables improves the capacity of the model to capture the spatial variation of the wellbeing scores. While some small areas still evidence slight over- and under-estimation of the model, these are much smaller than in the equivalent OLS models and are not statistically significant at the Global scale.

As the SE model predicting life satisfaction from greenspace types was the strongest, a semi-variogram displaying the improvement of spatial variance patterns in the data was created, thereby demonstrating the suitability of the spatial error regression in modelling this relationship. Supplementary Figure 4 displays the semi-variogram of the results of the original data (life satisfaction variable), the residuals of the fully adjusted OLS and SE models of greenspace type. This graph plots the average difference in residuals as the distance between two points increases, thereby representing the degree of spatial dependence (covariance) within the model results (Matheron, 1963). In line with the examination of Moran's *I* autocorrelations, this plot clearly demonstrates how the OLS model reduced the spatial dependence within the original data points, with the application of SE models were able to further capture the spatial processes within the residuals.

4 Discussion

4.1 Key findings

A large body of research into greenspaces and wellbeing is based upon the premise that exposure to nature may have salutogenic effects on individual and population health (Hartig et al., 2014) and planning guidance for urban development is often designed to provide residents with easy access to 'natural environments' (Natural England, 2010). In urban settings, this is generally facilitated through the provision of greenspace, which may take many forms. In fact, while many green features may appear 'natural', in an urban context they are often artificially constructed and maintained (Hartig et al., 2014).

Previous research has examined the association between various green qualities and health, using bespoke classification systems, usually designed in relation to a specific research question (Houlden et al., 2018) and only one study has been found which examined associations with multidimensional mental wellbeing (Wood et al., 2017); this study included less than 500 participants in a small region of Australia, although it did find positive associations between both natural and sport greenspaces and mental wellbeing.

Studies differ in their findings for the strength and significance of the association between greenspace and mental wellbeing, perhaps partly due to inconsistencies in characterisation of urban greenspace (Houlden et al., 2018). The current study was designed to investigate this variation by investigating associations with different types of greenspace. The UK's Planning Policy Guidance (PPG17) greenspace typology was used to ensure a robust, consistent classification of greenspace characteristics, including natural, park and sport areas within London.

To address another gap in knowledge, this study also calculated network distance between individuals and greenspace within 300m, indicating accessibility on foot. Only greenspaces greater than 2ha in area were included, to test the Natural England guideline that all individuals should be provided with 'a natural greenspace of at least 2ha within 300m walking distance of their home'; including a lower limit on the size of greenspace is common in other studies (Dadvand et al., 2016; Triguero-Mas et al., 2015). Dadvand et al.'s analysis, for example, included greenspaces of 0.5ha accessible within 300m as a binary variable; they identified a significant association with reduced risk of mental health issues, although satellite indicators of surrounding greenness (NDVI) revealed a stronger association (Dadvand et al., 2016). It may therefore be interesting for future studies to examine different size greenspaces and compare findings across these.

Using three mental wellbeing measures, associations were modelled for the amount of different types greenspace (natural, parks, sports, other) with life satisfaction, worth and happiness. In Spatial Error Models, results revealed that access to natural greenspace was positively and statistically significantly associated with both life satisfaction and happiness;

no other significant associations were identified. The autoregressive parameter, λ, indicated small but significant spatial patterns in the residuals and effectively captured the underlying local variation in error.

These findings provide some evidence that natural greenspace is the most strongly associated with mental wellbeing, and implies that the association between greenspace and health may be partly due to Biophilia, but opens up further questions regarding the significant results only for life satisfaction and happiness (hedonic wellbeing), but not sense of worth (eudaimonic wellbeing). While most previous research on mental wellbeing has focused only on life satisfaction (Vemuri et al., 2011), this study contributes to the evidence for the association between natural greenspace and hedonic wellbeing, although the findings on eudaimonic wellbeing remain inconclusive.

Further research is required to examine the relationship between greenspace characteristics and eudaimonic wellbeing in particular. It could be suggested that natural greenspace is important for hedonic wellbeing, as it may have the potential to alter individuals' immediate feelings, by improving mood (Molsher and Townsend, 2016), reducing stress (Ulrich, 1986) and restoring attention (Kaplan, 1984). Eudaimonic wellbeing, however, focuses on life meaning and achievement, which might be less related to natural greenspace in particular, but more generally associated with positive, potentially green, living environment (Barton et al., 2015). The data available included only one measure of eudaimonic wellbeing, which, while offering an insight into the two dimensions of wellbeing, is more simplistic than other scales built on multiple items, which may provide a deeper understanding of the relationship between nature and multidimensional mental wellbeing.

There may also be further characteristics of greenspace, such as usage patterns, facilities and objective quality, which may be associated with mental wellbeing, while individual-level attributes such as social connections and physical activity may further moderate these relationships (Lachowycz and Jones, 2013). Future studies should therefore seek to examine these qualities, to support the robust evidence required for greenspace design in urban settings.

4.2 Strengths and limitations

With Natural England recommending natural greenspace to be included close to urban residents' homes, as far as the authors are aware this is the first study to test this guideline by examining associations between different types of greenspace within a 300m walking distance of individuals. This study benefited from the inclusion of a strategic and justified classification of greenspace types, allowing quantities of natural greenspace to be compared to parks, sports spaces, and other greenspaces. This also provides some insight into the potential mechanisms, as different types of greenspace offer different opportunities. While this research focused on the most commonly studied categories of greenspace, analyses which allow for the consideration of a broader range of greenspace types would be welcomed in future studies.

While other studies examine greenspace prevalence and local area or even Euclidean buffer level (White et al., 2013; Maas et al., 2009), this research was also able to characterise the total amount of greenspace within a 300m walking distance, using network analysis of GIS shapefiles. Due to the granular level of data available, this network distance was calculated starting at the postcode centroid, an assumption which may over- and under-estimate the absolute distance in different cases. Greenspaces were also considered ‘accessible’ if their boundary could be reached within the specified distance, which may overlook the importance of entrances, which were not available within the GiGL data.

SE models were selected after examining the patterns in the residuals of OLS models and, by accounting for second-order spatial processes in the structure of the data, allowed the association between natural greenspace and mental wellbeing to be investigated. However, as with all models, assumptions regarding the structure of the data are made; in this case, that the clustering of residuals was due mostly or wholly to error processes that increase the probability of residual values to be similar to the ones in neighbouring locations. While enabling detailed individual-level analyses to be performed, other methods, such as Floating Catchment Areas (FCAs), which are more complex gravity-based models of spatial interactions, may allow consideration of high-order spatial patterns, across individual and local area levels (Wu et al., 2018).

Although restricted to London, this analysis benefitted from a large sample size of over 25,000 individuals, from the APS, which contains detailed socio-economic individual level data, as well as each individual’s postcode. These findings, while insightful and statistically significant, are based on data from London only, and should be interpreted with caution when considering the rest of the UK, or further afield. Further research is therefore needed to explore these relationships in more detail, as well as expanding studies to other areas of England. At the time of performing these analyses, mental wellbeing questions were asked of only half the APS sample, which may also limit the representativeness of the results; from

2018 onwards, this data is available for the whole sample, providing a larger dataset which will provide more detail for future study. The APS measure provides information on hedonic and eudaimonic wellbeing; however, as previously discussed, its multidimensionality may be limited by including one item for eudaimonia. Future research may benefit from including greater numbers of questions to examine these dimensions more holistically.

Since undertaking this research, Ordnance Survey have released the MasterMap Greenspace product, which comprises shapefiles of urban greenspaces across Great Britain, providing an opportunity for future analyses covering a broader spatial area (Ordnance Survey, 2017b). Other potential sources of data include OpenStreetMap, a volunteered, open-access data source, which is available internationally. Although reasonably accurate greenspace shapes are easily available, and have been effectively applied in other research (Haklay, 2010), they may be less reliable in areas of greater socio-economic deprivation (Mitchell et al., 2011). The features themselves are classified according to the contributor's judgement and are therefore not consistently categorised for studies of typology, which was the main area of interest for this study (OpenStreetMap contributors, 2018). However, these data may provide future opportunities for future study of total greenspace in large-scale analyses.

Only greenspaces with an area greater than 2ha were included in this analysis, in line with Natural England's recommendations for 'accessible greenspace'; this also had the advantage of simplifying the computational intensity and improving time efficiency of the calculations, and has been used by other studies of greenspace accessibility (Triguero-Mas et al., 2015). However, it may over simplify the issue of accessibility, as greenspaces smaller than this may still be useful and have an effect on mental wellbeing. While more challenging to accomplish, future analyses which include different limits of greenspace may provide further insight into which sizes and travel distances are most important for mental wellbeing, as well as allowing comparisons with other measures of greenspace accessibility.

Finally, the cross-sectional nature of the data provides no indication of causality or direction of these associations. Future longitudinal studies, which monitor mental wellbeing in those moving between environments with different greenspace qualities, may be able to provide more conclusive evidence of the effects of exposure to different types of greenspace on individual mental wellbeing.

5 Conclusions

The UK Government recommends that individuals should be provided with an accessible, natural greenspace of at least 2ha in size, within a 300m walk of their home; this is the first study of which the authors are aware to test the recommendation for its potential mental wellbeing benefit. Stratifying greenspace according to type, positive and statistically significant associations were observed for the amount of natural greenspace and hedonic wellbeing indicators of life satisfaction and happiness; associations with other types of greenspace were not statistically significant. Spatial Error models account for the second-order spatial clustering within the data, enabling robust estimations of these associations to be calculated, revealing slight but significant underlying geospatial processes within the structure of the data. Future studies might examine mental wellbeing, and eudaimonic wellbeing in particular, with a greater number of items, and characterise greenspace accessibility more thoroughly, by including greenspace access points and quality indicators. Studies which are able to consider the relationships not just in London, but across other cities in the UK, may also support this research by determining whether these patterns may be more widely generalisable.

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