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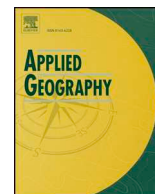
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A spatial analysis of proximate greenspace and mental wellbeing in London

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ABSTRACT

While local-area greenspace is associated with reduced symptoms of mental distress and greater life satisfaction, most previous research has measured the amount of local-area greenspace within administrative boundaries, and found mixed results for associations between greenspace and multidimensional mental wellbeing. The study was designed to examine whether the amount of greenspace within a radius of individuals' homes was associated with mental wellbeing, testing the government guideline that greenspace should be available within 300 m of homes.

Individual and Household-level data were drawn from the Annual Population Survey at postcode level (APS, Pooled Dataset 2012–2015), which includes 3 mental wellbeing measures, covering aspects of life satisfaction, sense of worth, and happiness, as well as a range of socio-demographic variables. Greenspace data were obtained Greenspace Information for Greater London Group (GiGL), and was used to calculated the amount of greenspace within a 300 m radius of individuals. Linear regression models revealed positive and statistically significant associations between the amount of greenspace and indicators of life satisfaction and worth. Moran's I, an indicator of spatial autocorrelation, revealed statistically significant clustering of the residuals of these models, so Geographically Weighted Regression (GWR) models were calculated, in order to adjust for underlying spatial processes within the data and investigate the geographic variation in the association between local greenspace and mental wellbeing. The global GWR model revealed that an increase in 1 ha of greenspace within 300 m of residents was associated with a statistically significant 0.803 increase in life satisfaction, 0.740 and 0.521 for worth and happiness, respectively. This therefore provides some support for the inclusion of greenspace within 300 m of homes. Local GWR coefficients revealed slight variation in the strength of these associations across the study space. Therefore, further analyses are required to investigate whether the walking (network distance), absolute size, or type of each greenspace are able to explain this spatial variation.

1. Introduction

As urbanisation increases, policy makers and planners are being challenged to accommodate new residents in sustainable ways (Barton, 2010; Murray & Lopez, 2017), including through the provision of greenspace. Human beings may have an innate desire to affiliate with nature (Wilson, 1984), and exposure to greenspace is beneficial to health (Hartig et al., 2014), being associated with improved attention (Kaplan, 1984), reduced stress (Ulrich et al., 1991) and greater feelings of happiness (White et al., 2017). These effects may be mediated through facilitating physical activity (Lachowycz & Jones, 2013; Maas et al., 2008; Mitchell, 2013; Sugiyama et al., 2008) or social interaction (Dempsey, Brown, & Bramley, 2012; Kaźmierczak, 2013). United

Nations Sustainability Goals (SDGs) focus on providing access to green spaces (Goal 11) and improving health and wellbeing (Goal 3) (United Nations, 2015). A recent UK government White Paper emphasised the importance of access to the 'natural environment' (Pinto et al., 2017), and the World Health Organisation stressed the importance of urban greenspaces to sustainable cities (World Health Organisation, 2016). Although the required amount and proximity of greenspace are not known, the UK government and European Union both recommend that greenspace should available within 300 m of homes (Natural England, 2010; Planning Policy Guidance, 2002).

Urban greenspace is any area of grass or vegetation which is deliberately set aside for environmental, aesthetic or recreational purposes (Houlden, Weich, & Jarvis, 2017; Taylor & Hochuli, 2017). While

local-area greenspace is associated with reduced symptoms of mental distress and greater life satisfaction (Alcock et al., 2014; Douglas and MikeScott, 2017; Hartig et al., 2014; White et al., 2013), few studies have examined associations with mental wellbeing in its broadest sense, including both hedonic (happiness) and eudaimonic wellbeing (purpose, fulfilment and self-worth) (Henderson & Knight, 2012; Ryan & Deci, 2001). Most research concerning greenspace and mental health has tested associations between the amount of local-area greenspace within administrative boundaries (Alcock et al., 2014; Ambrey, 2016; Lachowycz & Jones, 2013; White et al., 2013) and symptoms of either mental distress, happiness or life satisfaction (hedonic wellbeing), revealing that administrative-level greenspace may be associated with some aspects of health. However, studies which examined associations between hedonic and eudaimonic mental wellbeing and the amount of greenspace within administrative boundaries found no statistically significant associations (Houlden et al., 2017; Ward Thompson, Aspinall, & Roe, 2014; White et al., 2013; Wood et al., 2017). Studying greenspace in this way may misclassify exposure because greenspace may be present in adjacent areas, and because this ignores access, use and type of greenspace. Studies using areas centred on each participant's place of residence go some way towards addressing this (Bjork et al., 2008; Bos et al., 2016; Dadvand et al., 2016; Maas et al., 2009a; Maas et al., 2009b; Triguero-Mas et al., 2015; Van den Berg et al., 2010), though no studies have yet tested associations between the amount of greenspace estimated in this way and hedonic and eudaimonic wellbeing.

There are other challenges to the study of green space and mental wellbeing. Both vary spatially; moreover, those who live in greener areas may spend more time in greenspace (Coombes, Jones, & Hillsdon, 2010; Hartig et al., 2014; Maat & De Vries, 2006; Nielsen & Hansen, 2007), feel a stronger connection with nature (Cohen-Cline, Turkheimer, & Duncan, 2015; Irvine et al., 2013; Kamitsis & Francis, 2013) or value local greenspace more highly than those who live in less green areas (Cohen-Cline et al., 2015; Irvine et al., 2013; Lachowycz & Jones, 2013). Those who value greenspace more highly may be more likely to move to greener areas (Giles-Corti et al., 2008; Maat & De Vries, 2006). For this reason, it is also possible that the association between greenspace and mental wellbeing varies between people and between areas (Carrus et al., 2015; De Vries et al., 2003; Nielsen & Hansen, 2007; Taylor, Hahs, & Hochuli, 2018). Techniques such as Geographically Weighted Regression (GWR) adjust for this non-stationarity and permit model parameters to vary over space, thereby allowing variations in the associations between people and places to be estimated and modelled (Brunsdon et al., 1996, 1998; Chen & Truong, 2012; Hu et al., 2012; Waller et al., 2007).

Our aim was to investigate associations between individual-level greenspace and hedonic and eudaimonic wellbeing using spatial methods. We also tested the hypotheses that (a) surrounding greenspace is positively and significantly associated with mental wellbeing, and (b) that the association between nearby greenspace and mental wellbeing varies spatially.

Using GWR to capture second-order processes and model the associations between greenspace and mental wellbeing in London, it was found that the amount of greenspace within 300 m of individuals' homes was positively and statistically significantly associated with hedonic and eudaimonic wellbeing. Spatial variation in the strengths of the coefficients implies that the importance of greenspace may also differ across the city.

2. Methods

2.1. Sample and setting

Data were drawn from the Annual Population Survey (APS) pooled dataset April 2012–March 2015 (Office for National Statistics Social Survey Division, 2016). The APS, undertaken by the UK's Office for National Statistics, is a quarterly survey of households in Great Britain and Northern Ireland, in which areas are first stratified by postcode, then systematically sampled from a random start. The quarterly samples add approximately 15,000 individuals from 8700 UK households to the set, using initial face-to-face and follow-up telephone interviews for each participating individual in the household. The original UK sample for the 2012–2015 APS dataset was 567,481 individuals, a response rate of approximately 55% for the pooled data, which is combined at the end of the survey period. As greenspace data availability restricted analyses to Greater London, the final dataset comprised 25,518 individuals. Variables in the dataset cover aspects of wellbeing, demography, socio-economic status, and living conditions. The dataset also includes spatial identifiers (full postcode) and LSOA (Lower Layer Super Output Areas, an administrative district). There are 4844 LSOAs in London, with an average area of 0.33 km^2 and population of 1700 (Greater London Authority, 2014). These identifiers were used to link to local-area deprivation and population density at the level of individual respondents.

2.2. Study variables

2.2.1. Mental wellbeing

Mental wellbeing variables were based on three (of 4) questions developed by the Office of National Statistics (ONS) (Dolan, Layard, & Metcalfe, 2011) for monitoring mental wellbeing in the UK (Office for National Statistics Social Survey Division, 2016). They ask: "Overall, how satisfied with your life are you nowadays?", "To what extent do you feel the things you do in your life are worthwhile?" and "How happy did you feel yesterday?", with responses rated on a scale of 0–10. These questions are designed to cover hedonic (life satisfaction, happiness) and eudaimonic (worth) mental wellbeing. Data based on the fourth ONS wellbeing question, "how anxious did you feel yesterday?", were not used as these were considered to reflect mental distress rather than mental wellbeing.

2.2.2. Individual and household-level covariates

Potential confounding factors were included at individual level, including age, sex, marital status, ethnicity (using Census categories), and education. Health was ascertained using two items: self-reported general health and disability. Socio-economic status was assessed by income (in quintiles based on gross pay) and housing tenure. Living circumstances were characterised by living with children and housing type (detached house, semi-detached house, terraced house, flat/maisonette, other) (Office for National Statistics Social Survey Division, 2016).

2.2.2.1. Local area characteristics.
Local area data were retrieved from the London Data Store, providing population statistics and Indices of Multiple Deprivation (IMD) for each London LSOA, applied here as local area-level covariates (Department for Communities for Local Government, 2010; Greater London Authority, 2014). IMD scores were calculated across a number of domains including local education, crime and access to services, with a higher score indicative of a more deprived LSOA. Population density was calculated by dividing the number of residents in each LSOA by its area.

2.2.3. London maps

The Code Point map was obtained from Ordnance Survey, and provides locations for each postcode in London (Ordnance Survey, 2017). This was used to provide the spatial coordinates for each individual postcode.

2.2.4. Greenspace

Greenspace data were obtained from Greenspace Information for Greater London (GiGL), who collate data from London Borough councils. The dataset comprises GIS (Geographic Information System) shape

files with greenspace polygons describing the shape, size and location of 20,000 public greenspaces in London (Greenspace Information for Greater London CIC, 2017). The location of each greenspace allow them to be spatially linked to the other data files.

To calculate the quantity of local greenspace in the vicinity of the home of each participant, the data was preprocessed with the GIS tools ArcGIS (ESRI, 2011) and R (Theoundation for Stat, 2014). Firstly, Euclidean (straight-line) distance buffers were generated, by drawing a circle around the centroid of each individual's postcode, at a radius of 300 m. This buffer was then spatially intersected with the GiGL data, which was used to calculate the total amount (m^2) of greenspace area within 300 m of each individual's homes.

3. Analysis

Analyses were undertaken using both ArcGIS and R software (ESRI, 2011; Theoundation for Stat, 2014). Distributions of the greenspace and mental wellbeing variables, as well as the characteristics of the study sample, were examined.

To first investigate the linear association between the amount of surrounding greenspace and mental wellbeing, univariate Ordinary Least Squares (OLS) regression models were created for the association between the amount of greenspace within 300 m and each of the wellbeing questions in turn (life satisfaction, worth, happiness).

After testing for bivariate associations between each of the individual variables and mental wellbeing and the amount greenspace within 300 m in turn, the following were significantly associated with both, and thus included in the models as potential confounders: age, sex, marital status, ethnicity, general health, education, employment status, income, living with children, housing tenure, housing type, LSOA population density, and LSOA deprivation. Multicollinearity tests revealed all of the potentially confounding factors to be sufficiently independent. OLS multivariate models were then built, which include all socioeconomic and local area variables identified as potential confounders. Baseline models, including only these factors, were calculated, so the contribution of adding greenspace indicators could be observed.

Tests of spatial autocorrelations were then undertaken. Spatial autocorrelation refers to the degree to which attributes of objects are significantly clustered spatially, and leads to a risk of underestimating errors and overestimating the statistical significance of regression coefficients in a model (Haining & Haining, 2003). A K nearest neighbours (KNN) approach was implemented, using Euclidean (straight-line) distance between individuals' postcode centroid, to identify the closest N points for each individual, in turn. Taking the standard approach, the rounded square root of the number of instances (25,518) as K, 160 nearest neighbours were selected. The Global Moran's I statistics was then used to measure spatial autocorrelation between each of the mental wellbeing measures in turn; this method compares the actual

wellbeing value for each individual to a distance-weighted matrix of neighbours, and returns a value for the overall spatial clustering of the data (Li, Calder, & Cressie, 2007; Moran, 1950). Local Moran's I was then investigated, which provides a clustering value for each individual in the dataset, by comparing the value of each wellbeing measure to that of its 160 nearest neighbours (Li et al., 2007; Moran, 1950). Both measures output a value between -1 (perfect dispersion, where differing values cluster) and 1 (perfect clustering, where higher or lower values cluster), with a value of 0 indicating no autocorrelation.

The residual errors of the OLS models were also investigated, revealing significant spatial clustering, and highlighting how the model systematically over- and under-estimates the associations, implying geographic variation across the study space.

As with previous studies of the environment and health (Chen & Truong, 2012; Hu et al., 2012), Geographically Weighted Regression (GWR) was therefore selected as an appropriate method to adjust for these evident underlying spatial processes, and investigate the geographic variation in the association between local greenspace and mental wellbeing (Chen & Truong, 2012; Hu et al., 2012; Waller et al., 2007). The GWR method calculates a localised regression using distance-based weighting for each point; this method is essentially therefore a regression model in which the coefficients are allowed to vary over space (Brunsdon et al., 1996, 1998).

$$MWB_i = \beta_0 + \beta_1 GS_{1i} + \cdots \beta_m x_{mi} + \varepsilon_i \quad for \quad i = 1, ..., n \tag{1}$$

$$MWB_i = \beta_{0i} + \beta_{1i} GS_{1i} + \cdots \beta_{mi} x_{mi} + \varepsilon_{mi} \quad for \quad i = 1, ..., n \tag{2}$$

Equation (1) represents an OLS regression, where 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 greenspace within a specific buffer of the individual i's postcode centroid, and $\beta_m x_{mi}$ and ε_0 represent the contribution of the potentially confounding factors and an error term, respectively. Geographically Weighted Regression, however, allows these correlation coefficients β_{ni} to vary spatially, generating a separate model for each event location $\mathbf{u}$ in the data set, as demonstrated in Equation (2). Therefore, MWB_i is the predicted value of individual i's mental wellbeing score for the model centred around i, β_{0i} is the calculated constant, β_{1i} is the greenspace coefficient at location i, etc. Using the standardised approach, a Gaussian distribution was assumed for a kernel, which is used to calculate the weights assigned to the data points surrounding the individual i, to build the GWR model.

The kernel bandwidths for Geographically Weighted Regression define the radius within which the model searches for neighbours to include in each regression; larger bandwidths therefore include a wider area. These values are selected using leave-one-out cross validation to maximise the fit, and minimise residuals in each model, and were calculated for the association with the amount of greenspace within the 300 m buffer, and were determined as follows: 1,596 m for life
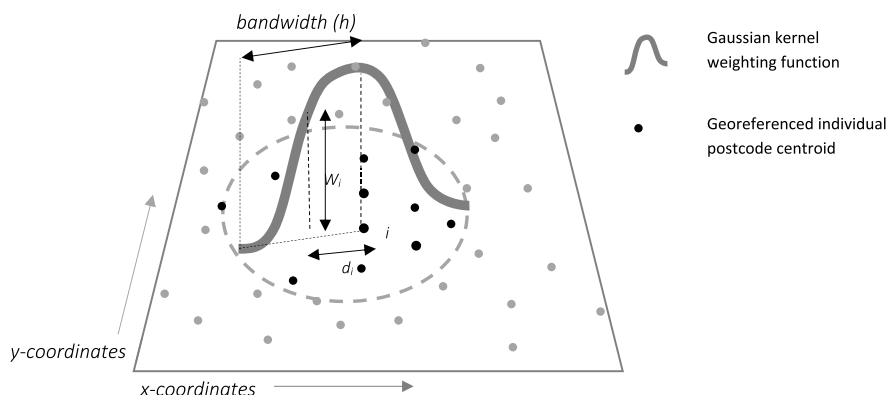

Fig. 1. Demonstration of Geographically Weighted Regression calculations.

Table 1
Full descriptive statistics of the sample.

Variable	Value	n	Mean(sd)/%
Wellbeing	Life Satisfaction	25,518	7.4 (1.8)
	Worth	25,518	7.7 (1.7)
	Happiness	25,518	7.3 (2.1)
Age Group	16–24	1734	6.8
	25–34	5014	19.6
	35–44	5321	20.8
	45–54	4590	18.0
	55–64	3670	14.4
	65–74	3010	11.8
	75+	2179	8.5
Sex	Female	14,201	55.7
Married/Cohabiting	Yes	13,655	53.5
Ethnicity	White	17,099	67.0
	Black	2737	10.7
	South Asian	2721	10.7
	Other Asian	1050	4.1
	Mixed	484	1.9
	Other	1427	5.6
Diploma/Degree	Yes	10,348	40.6
General Health	Very Good	8703	34.1
	Good	10,512	41.2
	Fair	4722	18.5
	Poor	1229	4.8
	Very Poor	352	1.4
Work Limiting Health Status	Yes	2730	10.7
Economic Activity	Employed	15,077	59.1
	Unemployed	1284	5.0
	Inactive	9157	35.9
Full Time Employment	Yes	11,098	43.5
Income Quintiles	1	2018	7.9
	2	2020	7.9
	3	2103	8.2
	4	1946	7.6
	5	1978	7.8
Living With Children	Yes	8758	34.3
Housing Tenure	Owns Home	6469	23.4
Housing Type	Detached	774	3.0
	Semi-Detached	2566	10.1
	Terraced	5454	21.4
	Flat	7508	29.4
	Other	9216	36.1
LSOA Variables	IMD	25,518	23.3 (12.5)
	Population Density	25,518	97.9 (63.7)
Greenspace Area, m^2	300 m buffer	25,518	45,232.6 (38,461.7)
	500 m buffer	25,518	151,444.6 (103,103.2)
	1 km buffer	25,518	727,158.0 (373,533.6)

satisfaction, 2,639 m for worth, and 3,149 m for happiness. The process of weighting the data with a moving kernel is demonstrated in Fig. 1.

Univariate GWR models were calculated for each of the greenspace buffers and mental wellbeing measures in turn, and then adjusted for the full set of potentially confounding factors, as with the OLS models, using the *spgwr* package in R. As this technique runs a localised regression around each data point (individual), the output provides the distribution of the 25,518 coefficients; the global value is taken as the general coefficient. One-sample t-tests were used to estimate the statistical significance of the global coefficient for each predictor variable.

Autocorrelations of the residual errors were then examined, to investigate improved fit from the OLS to GWR models, and to demonstrate the contribution of the addition of greenspace to the model.

4. Results

There were 25,518 residents of greater London in the final sample. Mean wellbeing scores were fairly consistent across the three questions (life satisfaction 7.4 (sd 1.8), worth 7.7 (sd 1.7), and happiness 7.3 (sd 2.1)). The amount of greenspace within a 300 m buffer had a mean of 0.045 km^2. Full characteristics of participants are shown in Table 1.

Results of the OLS models, shown in Table 2, revealed positive and statistically significant associations between the amount of greenspace within 300 m and all three wellbeing measures. However, after adjusting for all individual and local level potentially confounding factors, only the models predicting life satisfaction and worth were statistically significant.

Global Moran's *I* tests detected very small, but statistically significant (at the 95% level) global autocorrelation of the residuals for each of these models (values of 0.005, 0.003 and 0.001 for life satisfaction, worth, and happiness, respectively). Local Moran's *I* results also revealed statistically significant spatial clustering of the OLS results, as demonstrated in Fig. 2a–c, which demonstrate the locations and directions of this clustering. The clusters of low and high residual values highlight areas where the OLS models systematically over- and under-estimate the associations between greenspace and wellbeing, across the study space. In the life satisfaction model, for example, high residuals towards the centre of London indicate the model over-estimating mental wellbeing, with predictions falling short towards the North and East of the city.

Coefficients for greenspace variables calculated with GWR models are presented in Table 3, for both univariate and fully adjusted models; full results tables for each of the models are provided as Data in Brief (Houlden et al.). In Table 3, the *B* value represents the mean value of the regression coefficient, *β,* indicating the expected increase in wellbeing score for a 1 km^2 increase in greenspace provision within each buffer.

Positive and statistically significant associations were observed for the amount of greenspace within 300 m and life satisfaction, worth, and happiness, with *B* values of 0.8034, 0.7398 and 5.208, respectively. Models predicting life satisfaction showed much higher goodness of fit, as indicated by the R^2 value (0.305), than the other wellbeing indicators (0.170 for worth, 0.136 for happiness). Sensitivity analyses revealed coefficients which became weaker with distance, with results tables provided as Data in Brief (Houlden et al.). For life satisfaction, for example, the greenspace coefficient was reduced to 0.3300 at 500 m, approaching 0 at a radius of 1 km (0.0421). Similar patterns were observed for both worth and happiness.

These *B* values are averages of the 25,518 coefficients output from the GWR model. To visually investigate the spatial variation in these associations, the coefficients for each model were mapped (Fig. 3a–c); the plots demonstrate strength variation in line with acceptable wellbeing outcome scores; coefficients vary from −10 to 10 for life satisfaction, and −6 to 6 for worth and happiness. However, the variation in the direction of these associations, which were negative in some areas, was unexpected, meaning that the model predicts higher, or in some places, lower wellbeing values to be associated with increased

Table 2
Results and greenspace coefficients for unadjusted and fully adjusted OLS associations between greenspace and mental wellbeing.

Greenspace within Buffer	Life Satisfaction B p		R^2	Worth B p		R^2	Happiness B p		R^2
300 m	0.601	0.037	0.013	0.874	0.002	0.020	0.299	0.382	0.005
300m, adjusted	*0.914*	*0.001*	*0.388*	*0.721*	*0.009*	0.307	0.508	0.142	0.288

OLS Residuals- Life Satisfaction

a

OLS Residuals- Worth

b

LISA clusters

☐ insignificant
■ low-low
■ low-high
■ high-low
■ high-high

LISA clusters

☐ insignificant
■ low-low
■ low-high
■ high-low
■ high-high

OLS Residuals- Happiness

c

LISA clusters

☐ insignificant
■ low-low
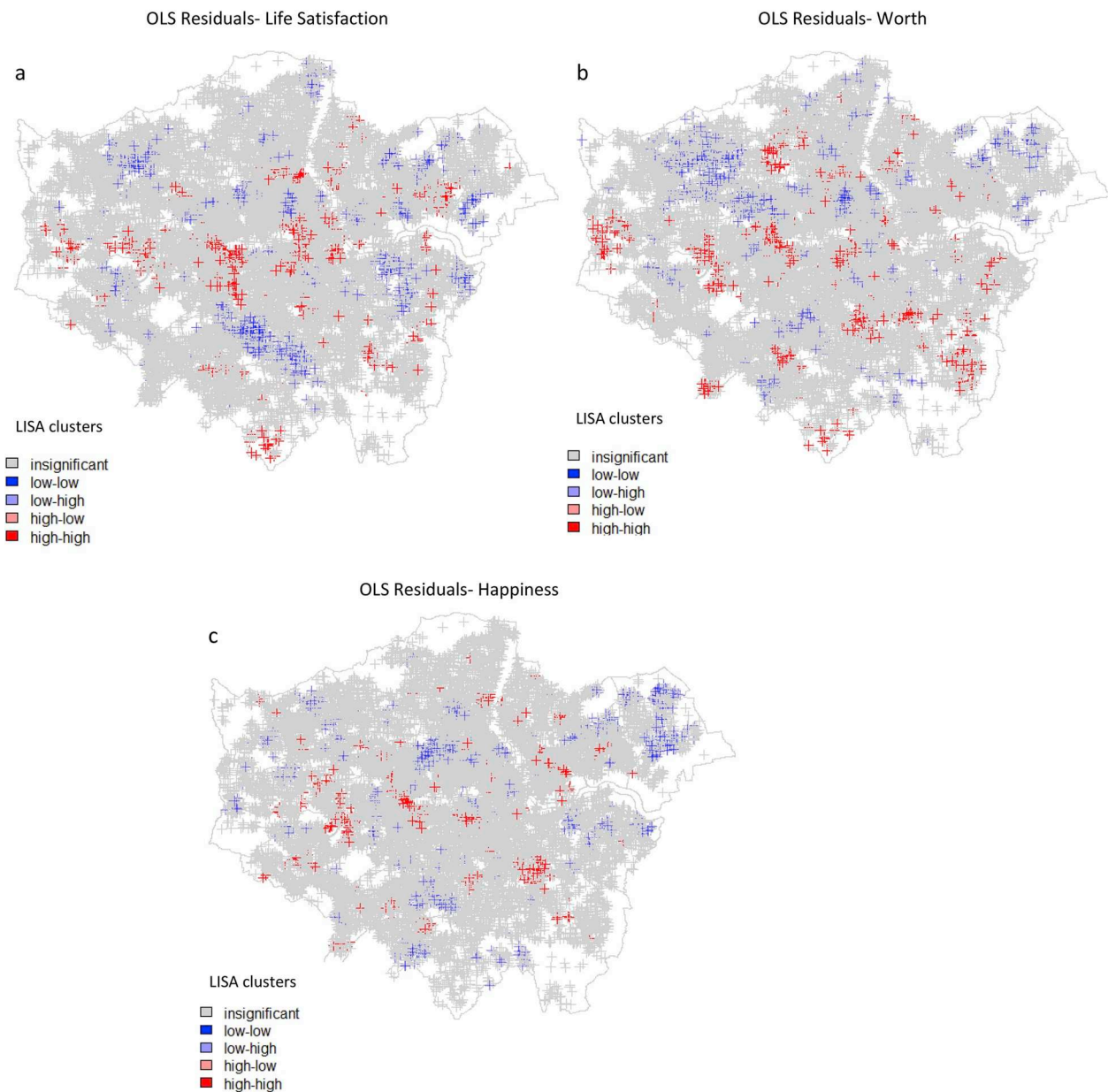■ low-high
■ high-low
■ high-high

Fig. 2. a-c Local Moran's I Autocorrelations of residuals in OLS models for the associations between greenspace within 300 m and (clockwise from top left): (a) life satisfaction, (b) worth, (c) happiness.

greenspace, in different areas.

Similar patterns of spatial variation can also be seen, particularly for associations between greenspace and worth and happiness, with lower β values generally observed towards the East of London. These visualisations therefore demonstrate the extent of the deviation in β values, and how geographically weighted regression models capture the spatial variation in associations between greenspace and mental wellbeing. For example, the greenspace and life satisfaction model (Fig. 3a), while overall significantly positive, show stronger positive regression coefficients in the North, West and South of London, with some areas

displaying negative associations towards the centre and East; this indicates how the importance of greenspace appears to be different in different regions.

Reductions in autocorrelations of residual errors highlighted that the GWR method effectively accounted for much of the spatial clustering in the data, and therefore considerably improved the fit of the model, for each wellbeing measure. The Global Moran's I value from the residual errors of a model predicting life satisfaction from just the potentially confounding factors was reduced from 0.005 to < 0.001 when adding the variable for the amount of greenspace within 300 m to a

Table 3
Results and greenspace coefficients for unadjusted and fully adjusted GWR associations between greenspace and mental wellbeing.

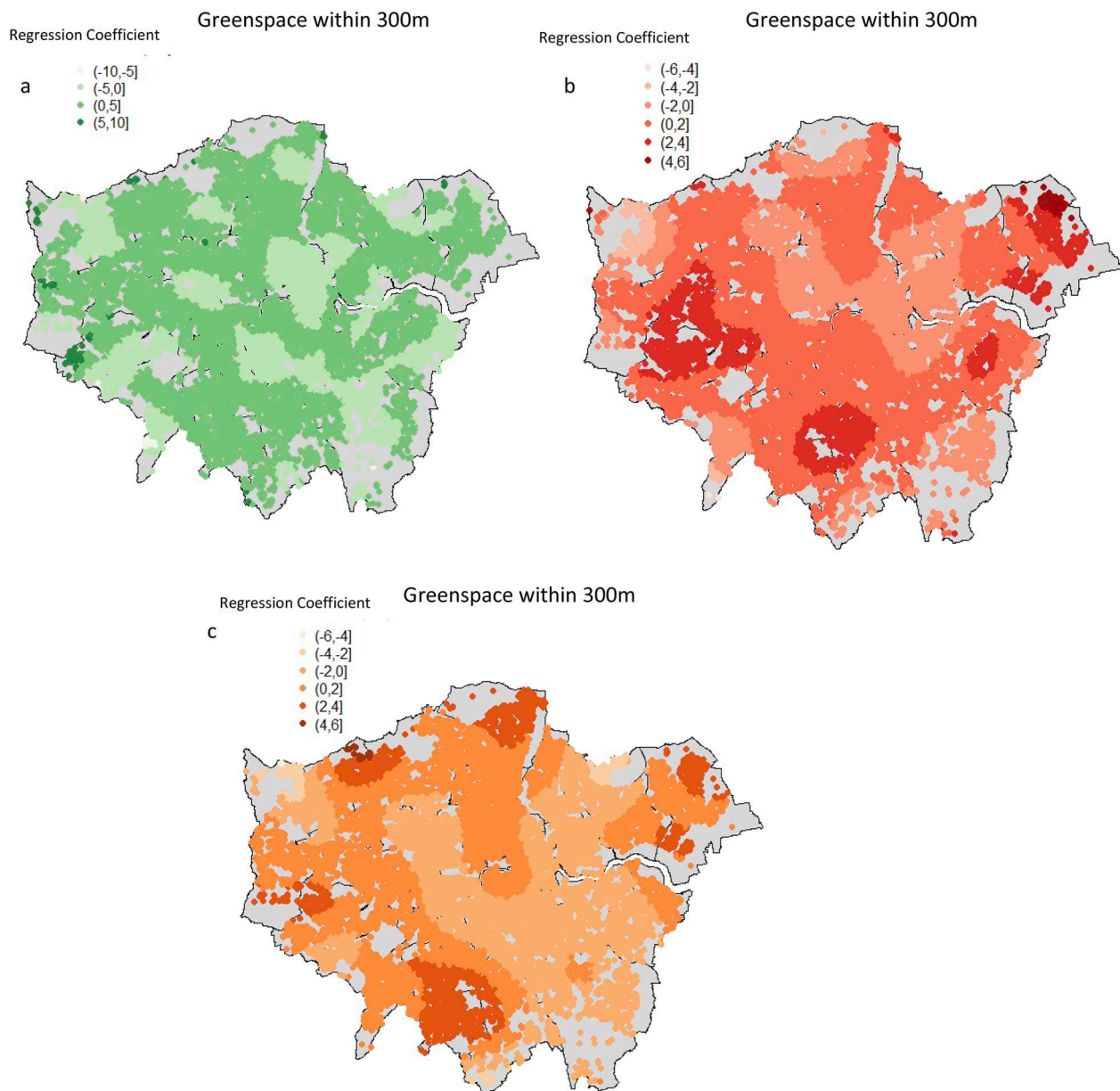| Greenspace within Buffer	Life Satisfaction B p		R^2	Worth B p		R^2	Happiness B p		R^2
300 m	0.4840	< 0.001	0.012	0.8212	< 0.001	0.010	0.2985	< 0.001	0.010
300 m, adjusted	*0.8034*	*< 0.001*	*0.305*	*0.7398*	*< 0.001*	*0.170*	*0.5208*	*< 0.001*	*0.136*

Fig. 3. a–c Geographically Weighted Regression Coefficients, for associations between greenspace and (a) life satisfaction, (b) happiness and (c) worth.

GWR model; similar patterns were observed for models both with worth and happiness as the outcomes. Plots indicating the statistical significance and direction of Local Moran's *I* for each of these associations are available separately (Houlden et al.). There was clear reduction in the residual error local autocorrelations when compared to the linear model equivalents shown in Fig. 2a–c, which demonstrates that the addition of greenspace as a variable improves the capacity of the model to capture the spatial variation of the wellbeing scores.

5. Discussion

A large body of evidence has previously linked local prevalence of greenspace to improved health outcomes (Douglas and MikeScott, 2017; Hartig et al., 2014; Lachowycz & Jones, 2013), with many studies agreeing that mental health may be improved for those living in greener areas (Gascon et al., 2015). While studies of positive mental health have found associations between surrounding greenness and aspects of mental wellbeing such as life satisfaction and quality of life (Ambrey, 2016; Ambrey & Fleming, 2014; Vemuri & Costanza, 2006; White et al.,

2013), results of analyses using measures of both hedonic and eudaimonic wellbeing have so far remained inconclusive (Houlden et al., 2017; Ward Thompson et al., 2014; White et al., 2017; Wood et al., 2017). However, these multidimensional studies have generally been restricted by their application to count the greenspace areas that exist within pre-defined administrative boundaries (e.g. census areas such as LSOAs), rather than the actual greenspace area that surrounds an individual's home. This may have misclassified residents and masked associations, particularly if they live close to the border of census units that have greenspace in their neighbouring areas (Houlden et al., 2017). Unlike these studies, this analysis measures greenspace at the individual level, and was able to detect significant associations.

Using the three mental wellbeing measures, distributed through the UK's Annual Population Survey, this study examined the associations between greenspace at various distances from individuals' postcodes, and their hedonic and eudaimonic wellbeing, in London. Prevalence of greenspace was positively and significantly associated with measures of hedonic and eudaimonic wellbeing. Associations with life satisfaction showed the best fit, as well as the highest regression coefficients,

suggesting that greenspace may be most important for this aspect of mental wellbeing.

These findings therefore begin to provide some evidence that government guidelines recommending greenspace provision within 300 m of homes may be appropriate in designing for mental wellbeing, in London. With the strongest association detected for this distance, this suggests that closer greenspace may be more important for mental wellbeing, and life satisfaction in particular, than greenspaces located at greater distances from individuals.

Visually examining the distribution in GWR coefficients also revealed that the strength of association varies across the study space. Regression coefficients appeared higher towards the outskirts of London, with slightly weaker, and sometimes negative associations observed towards the centre. These results imply that the association between greenspace and mental wellbeing is not static, and, although overall positive for these measures, the strength and direction may further depend on the individual people and places. For example, the stronger, positive associations towards the edge of London may be due, in part, to differences in greenspace composition to that in the centre. It could be speculated that central greenspaces are typically in the form of parks, but may be larger or more natural, as the area becomes less urban, which may be features important for mental health and wellbeing (Hartig et al., 2014). It could be suggested that other factors, such as the type, accessibility and use of greenspace, which were not captured in these analyses, may also be beneficial, and future studies should try and further capture these characteristics, although data availability is a big challenge for this. Further, although we adjusted for a number of individual and sociodemographic confounding factors, it is possible that there may be complex interactions between these other variables and availability of greenspace, which would be worthy of further investigation.

5.1. Strengths and limitations

While the UK Government have guidelines on greenspace provision, to the best of our knowledge, this is the first study to provide some evidence for government greenspace recommendations, for mental wellbeing. We were also able, by generating buffers at multiple distances around the individual's postcode, to observe how these associations changed for greenspace prevalence at increasing distances, giving insight into a potential dose-response effect.

Previous studies have tended to examine relationships between greenspace and health using non-spatial techniques, such as linear or logistic regression (Houlden et al., 2018), which are prone to be threatened by the spatial dependence of the relationships between greenspace and health. This is the first study of which we are aware which has applied spatial methods, to account for the inherently geographic clustering of individual and greenspace prevalence data in relation to wellbeing. Results of both linear and geographically weighted regressions (GWR) highlight that accounting for the underlying spatial processes may reveal associations which traditional methods may not be capable of detecting. The GWR models effectively captured the spatial heterogeneity in the data, and suggested that such associations may vary across the study region, implying that, greenspace may be more important for wellbeing in some areas, than others. The causes of these differences, which may include further individual or environment characteristics, should be the subject of future analyses.

Although restricted to London, this analysis benefitted from a large sample size of over 25,000 individuals, from the Annual Population Survey, which contains detailed socio-economic individual level data, as well as each individual's postcode centroid. This allowed a comprehensive dataset to be generated by merging information from local-area, greenspace and individual sources. We were also able to control for a large range of potentially confounding factors, from socio-economic status to health, living conditions, local area deprivation and population density. 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.

This analysis also benefits from the application of individual-level, rather than traditional local-area level greenspace, which is more reflective of the living environment and has revealed associations between greenspace and multidimensional mental wellbeing which were not detected in previous research. However, Euclidean distance does not take account of actual travel distance, which may simplify how close individuals are to a greenspace in real terms, and limit the interpretation somewhat. Further, greenspace may take many forms, from parks to nature reserves and sports facilities; future analyses of these different types may reveal different associations. We were also not able to take account of factors such as accessibility, quality or facilities of the greenspaces, all of which may be associated with mental health outcomes (Lachowycz & Jones, 2013).

The APS measure provides information on self-reported hedonic and eudaimonic wellbeing; however, it only has one item (worth) relating to eudaimonic aspects. Other scales, such as the Warwick-Edinburgh Mental Well-Being Scale (WEMWBS), for example, provide up to 14 items covering aspects including feeling useful, relaxed, close to other people, dealing with problems well, thinking clearly, and able to make up one's mind, may be more holistic (Tennant et al., 2007). Although applied to population surveys such as the UK's Longitudinal Household Panel Study, this survey is not available in datasets as large as the APS.

It should also be considered that, although we selected geographically weighted regression to account for the spatial patterns in the data, and its application to such analyses is still fairly experimental, other, more complex methods such as Floating Catchment Areas (FCAs), or Autoregressive Models, might also be appropriate, and should be investigated in the future.

Finally, despite the depths and detail of this analysis, the cross-sectional nature of the data provides no indication of causality or direction of these associations. Cross-sectional studies may also subjected to selection bias, so future longitudinal/cohort studies should be conducted to observe the potential effects of greenspace upon mental wellbeing.

6. Conclusions

While many previous studies have failed to detect any association between greenspace in an individual's administrative local area and their mental wellbeing, this study applied weighted regression methods to account for underlying spatial heterogeneity and reveal a positive association between greenspace around homes and both hedonic and eudaimonic wellbeing. Positive, statistically significant associations were found for prevalence of greenspace within the recommended 300 m distance and mental wellbeing, while weaker associations at greater distances imply that greenspace closer to homes may be more important. Variation in the strengths of these associations highlights the fluctuating importance of greenspace for mental wellbeing in different areas of the city; coefficients were also found to be generally weaker in the centre of London, perhaps due to differing compositions of greenspace in different areas of the capital. While UK government guidelines recommend that greenspace should be provided within 300 m of all residents to benefit health, these results provide some evidence that this distance is also associated with higher levels of mental wellbeing. It may therefore be suggested that urban planners should be encouraged to include greenspace close to residents, for potential mental wellbeing benefits. Future studies should continue to adopt methodological approaches which consider the spatial nature of the data, and expand of this work by considering actual travel distances and different types of greenspaces.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2019.102036.

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