Abstract

Background: One cause of childhood obesity is a reduction in the amount of unstructured time spent outdoors, resulting in less physical activity. Greenspaces have the potential to increase children's physical activity levels, so it is desirable to understand how to create spaces that promote visitation and activity.

Objectives: We investigate the relationship between rates of obesity at ages 4-5 and 10-11 in small-area census geographies, and indicators of the neighbourhood greenspace environment, in the northern English city of Sheffield.

Methods: To capture the environment at scales relevant to children, we test the importance of overall green cover; garden size; tree density around residential addresses; and accessibility within 300m of any greenspace, greenspaces that meet quality criteria, and greenspaces with play facilities. We use a multi-model inference approach to improve robustness.

Results: The density of trees around addresses is significant at both ages, indicating the importance of the greenspace environment in the immediate vicinity of houses. For 10-11 year olds, accessibility of greenspaces meeting quality criteria is also significant, highlighting that the wider environment becomes important with age and independence.

Conclusions: More attention should be given to children's requirements of greenspace when considering interventions to increase physical activity or planning new residential areas.

Keywords

childhood obesity; urban greenspace; neighbourhood environment; greenspace accessibility; Sheffield, UK; health inequalities

1. Introduction

Childhood obesity is a major global public health concern affecting over 40 million children worldwide [1,2]. In the UK in 2014/15, 22% were overweight by school entry age (4-5 years), rising to 33% by age 10-11 [1]. Children who are overweight or obese are more likely to suffer from overweight and obesity as adults, and to suffer physical and psychological ill-health and a reduced quality of life both in childhood and as adults [2,3].

The causes of this obesity epidemic are varied and complex, but many are determined early in life, before the age of five. The earliest risk factors arise in the parents before conception, for example from parental body mass index (BMI) and diabetes status [2,4,5]. Maternal smoking, exposure to environmental pollutions, excess weight gain during gestation, and method of delivery, are also important risk factors [1,2,5]. Infancy is a critical time in the development of risk factors for obesity: both metabolic functioning and behavioural habits are set and modified most easily at this age [1,2,4]. Dietary factors – breastfeeding vs. formula feeding, age at introduction of solid foods, and food choices – are important, but so are parenting styles and quality of relationships with parents, physical activity, sleep, and use of antibiotics [1–5]. As the child ages, exposure to easy availability and marketing of high-energy foods also becomes a concern [1,3]. Stressful events in childhood may also increase the risk of obesity [6].Some of these risk factors are more modifiable than others.

One of the wider behavioural factors that has been linked with obesity is a lack of unstructured time spent outdoors and in nature, leading to what has been termed "nature deficit disorder" [7,8]. Children use free, unstructured time to play, which contributes to creative and social development and emotional health as well as to physical health via physical activity [8]. However, there have been recent decreases in outdoor unstructured play time accompanied by increases in indoor, sedentary activities [2–4,6]. There are a number of reasons for this decrease, including a perceived lack of safety outdoors, a lack of parental time to supervise outdoor activity, and the absence of suitable and age-appropriate spaces [3,9].

In this study, we focus on factors relating to the green aspects of the urban environment and relate these to incidence rates of childhood obesity. A number of studies have reported associations between the amount of greenspace near children's houses, or distance to a greenspace, and obesity rates [10–12]. However, not all greenspace has the same capacity to contribute to health and well-being [13,14]. Children have requirements of greenspace that are different to those of adults, and these requirements vary by age and gender [15,16].

One of the key interventions to prevent childhood obesity is encouraging higher levels of physical activity [4]. Given the potential of greenspaces to increase physical activity levels amongst children [4,8], it is important to understand which aspects of the neighbourhood greenspace environment contribute most. In addition to reducing obesity risk via promoting physical activity, providing a suitable greenspace environment for children may benefit their health via stress reduction and other emotional benefits [7,8], which may also reduce obesity risk [6]. There is therefore a need for population-level studies of associations between detailed indicators of the greenspace environment and obesity rates. Children generally experience a relatively limited spatial area on a day-to-day basis due to parental limits on independent travel, although this area may increase with age as the child's level of independence increases [9,17,18]. For this reason, indicators of the greenspace environment should focus on the areas closest to homes.

The aim of this study is to examine associations between small-area population rates of childhood obesity and several specific indicators of the local greenspace environment. Our data are captured at Lower-layer Super Output Areas (LSOA), a census geography used for reporting small area statistics. LSOAs have an average population of 1600, with an average of approximately 14-17 children per school year group. LSOAs are commonly used in research into relationships between health and greenspace [14,19]. They provide a suitable scale for investigating spatial patterns within cities while having an adequate population to reduce the risk of random statistical fluctuations and preserve anonymity for most types of health data. Sheffield's 345 LSOAs have an average area of 107ha; if they were circular, this would correspond to a radius of 329m. Whilst examining at the level of the individual would be preferable to avoid the potential issues of ecological studies, due to confidentiality concerns individual-level data pertaining to childhood obesity across an entire city are not usually available. We have obtained data at this relatively low level of aggregation through partnership with Sheffield City Council.

2. Methods

2.1. Study area

Sheffield is an ex-industrial northern English city located near the Peak District (53°23′N, 1°28′W). The city covers an area of 368km^2 and had a population in 2011 of 552,000. There is a substantial area of moorland and agricultural land within the western half of the city: only 50% of Sheffield's land area is classified as urban, although 98% of the population lives in these areas. Within the urbanised area, there is a strong west-east gradient of income and health deprivation. This has existed since the Victorian era, when the east end was heavily industrialised and housed working class neighbourhoods, while wealthier citizens lived in the cleaner west [20].

2.2. Obesity data

Our obesity data were supplied by Sheffield City Council. The data are LSOA counts of childhood overweight (BMI >= 85th centile of the British 1990 growth reference, UK90 [21], according to age and sex) and very overweight (BMI >= 95th centile; together termed obesity) for children in the first and final years of primary school, i.e. Reception year (abbreviated to YR, age 4-5) and Year Six (Y6; age 10-11). The data, collected as part of the National Child Measurement Programme, relate to the years 2013-2017 (aggregated to provide sufficient numbers for robust analysis). Children attending all state-run schools were included, excluding those not consenting or withdrawn by parents and children with growth disorders or Down syndrome. Weight was assessed using Class III scales, and height using a stand-on height measure, by staff trained by a medical professional. Children were asked to remove shoes and wear normal, light indoor clothing [22]. Table 1 shows details of population size and composition, deprivation levels and ethnicity for LSOAs divided into tertiles of obesity. Maps of obesity rates are shown in the Supplementary Material, Figure S1.

2.3. Greenspace variables

We use six greenspace indicators, selected on the basis of theory or previous studies suggesting an association with health, and also on the availability of suitable data.

<u>Green cover</u>, our simplest and broadest indicator of LSOA greenspace is green cover, quantifies the percentage of the LSOA that is under natural land covers (excluding that in private domestic gardens, which is captured separately). This follows other studies that have found a broad measure of local greenness to be important for childhood obesity [10–12]. This variable was derived from Ordnance Survey (OS) MasterMap (November 2017 issue), which maps all physical features in the environment that are considered to be important in the landscape. The indicator is the percentage of the LSOA under natural land covers, including water but excluding domestic gardens.

<u>Garden size</u>, our second indicator, is the mean size of private gardens averaged across residential properties within LSOAs, measured in m^2. Previous work has found that the

availability of gardens is related to childhood obesity [11]. Moreover, a substantial proportion of children's physical activity takes place in private gardens [23]. Gardens were identified from OS MasterMap. The total area of these within LSOAs was divided by the number of residential addresses, identified from OS AddressBase Plus (December 2017 data).

Tree density around homes is our third indicator. Studies have shown that trees in the local environment have positive effects on children's BMI/rates of obesity by promoting physical activity. In Houston, Texas, 9- to 11-year-old Hispanic children living in areas with more trees and larger areas of trees had lower BMI and a higher health-related quality of life [24]. Similarly, greater street tree density has been associated with lower obesity rates amongst 3- to 5-year-old children in New York City [25]. We measured tree density around individual residential addresses and then averaged across LSOAs. We used Bluesky's National Tree Map, which maps trees and shrubs over 3m in height. We calculated the density of trees within 100m of each address in GIS by creating a raster of the number of trees within a 100m circular radius of each 5m grid cell, and extracting the value of this raster at each address point. The radius of 100m was used as humans can readily grasp the scene around them at this scale [26], and 5m grid cells were used as the smallest houses in the study area are approximately $5m^2$. We also tested 50m and 200m radii and these were strongly correlated with values at 100m (Pearson's $r = 0.98$ and 0.97 respectively). Using 50m made no qualitative difference to model results but using 200m resulted in a poorer model fit due to failure to capture adequately fine scale variation.

The final three indicators relate to the accessibility of greenspaces from residential properties. Public greenspace accessibility is assessed as the proportion of addresses that are within 300m of at least one publicly accessible greenspace. 300m equates to approximately a five minute walk; this is the distance recommended by a recent literature review [27] and is also similar to the distances that most parents will allow children to travel independently [17,18]. This indicator is also measured at the level of individual addresses and averaged across LSOAs. This variable is the proportion of residential addresses that are within 300m by the transport network of an access point to a greenspace that is considered to have recreational or leisure value. Data on these 936 greenspaces were obtained from Sheffield City Council's 2008 green and open space assessment, and includes sports pitches, parks and gardens, (semi-)natural greenspaces, cemeteries/churchyards, allotments and community gardens, children's play facilities, and amenity greenspaces such as central greens in residential areas. However, it does not include rural open space. Full details of the calculation of all three accessibility measures are given in Mears et al. [20].

Good public greenspace accessibility is a similar measure that includes only greenspaces meeting three quality-related criteria that increase the likelihood of contributing to health [20]: size of at least 2ha, having a predominantly natural feeling, and received a 'good' or better quality rating in the 2008 assessment. These criteria indicate the ability of greenspaces to convey health benefits and also correlate with how well greenspaces are actually used [20].

Public greenspace with provision for children and young people accessibility, hereafter shortened to play facility accessibility, is the final accessibility measure. This is calculated using the same method as the previous two indicators, but includes only green and open spaces designed at least partly for children and young people's play and social interaction, as identified from the 2008 assessment. Such facilities, including playgrounds, games areas, and skate or bike parks, can increase visitation rates and physical activity levels amongst these age groups [15,16].

Descriptive statistics for the greenspace variables are shown in Table 2. None of the greenspace variables were highly correlated (maximum absolute Spearman's *rho* = 0.48), although garden size was strongly correlated with some controlling variables, especially address density (*rho* = -0.92). The full correlation matrix is shown in the Supplementary Material, Table S1.

2.4. Controlling variables

In order to minimise confounding in our models, we included two socioeconomic factors (income deprivation and air pollution) that influence health of children and are likely to correlate with aspects of the greenspace environment, and which have been included in other analyses of relationships between greenspace and health [13,19,28]. We also added an indicator of urbanicity (address density) following observations that the results of earlier versions of the model were confounded with levels of urbanisation. Descriptive statistics of controlling variables are shown in Table 2. The controlling variables are also shown in the correlation matrix in Table S1.

Income deprivation is used to control for socioeconomic deprivation. For this variable we used the income deprivation domain of the English Indices of Deprivation 2015, which is based on the number of individuals receiving various forms of state support. Note that this domain was used instead of the Index of Multiple Deprivation as it also includes a health domain, and so is likely to be confounded with obesity. We also did not use the income deprivation affecting children index as this has only been calculated at two time points, so its longer-term stability is less clear.

Air pollution is controlled for using the proxy variable of average modelled PM_{10} concentrations for 2010. These were derived from the Department for Environment, Food and Rural Affairs 1km grid model, with LSOA values calculated using unit postcode level population weighted averages.

Address density is the average density of residential addresses within 100m of each residential address. This was calculated using the same method used for tree density (Section 2.3) but using residential address points (from OS AddressBase Plus) instead of trees. Other distances (50m and 200m) were again highly correlated (Pearson's $r >= 0.97$) and their use did not result in substantially different model results.

2.5. Statistical modelling

One LSOA, which contains mostly student housing and has the highest address density but lowest income deprivation of all LSOAs, was excluded from analysis due to exerting a large influence on results. This left a sample size of 344. Following similar work by other authors [19], we used negative binomial regression to model the effects of the greenspace and controlling variables on obesity rates at YR and Y6. Poisson regression was rejected due to overdispersion. Expected rates of obesity, calculated using indirect standardisation for sex distribution, were included in models as an offset term (a term with an assumed coefficient of 1).

Given the large number of predictor variables, we used a multi-model inference approach following Symonds & Moussalli [29] and Richards et al. [30] to reduce the risk of overfitting. We first constructed a base model including only the offset term and linear terms for the controlling variables. We then tested all possible combinations of greenspace variables (linear and quadratic terms) plus quadratic terms for the controlling variables, following marginality rules (i.e. quadratic terms only included where linear terms are present). Quadratic terms were included because, although we hypothesised that each of the included variables would influence obesity rates, we did not have specific hypotheses for the shapes of the relationships. The multi-model inference approach facilitated inclusion of the quadratic terms where there was evidence from AICc (Akaike Information Criterion corrected for small sample size) values for curvilinear relationships, while preventing overfitting where evidence was lacking.

Orthogonal transformation was used to aid stability and ensure that the significance of linear and quadratic terms was independent. Due to the difficulty of interpreting coefficients from orthogonally transformed data (as they are not on 'real' scales), to aid interpretation we used coefficients from a version of the averaged model using untransformed data to draw plots of the marginal effects of each greenspace and controlling variable. Both averaged models used the same plausible set of models; data (non)transformation was the only difference. It should be noted that fitted values are identical regardless of whether untransformed or orthogonally transformed data are used.

From this full set of possible models we constructed a plausible subset of models within six AICc units of the model with the lowest AICc score, and excluding models that were more complex versions of models with a lower AICc score. Finally, the plausible set was averaged, imputing zero for coefficients not appearing in individual models in order to prevent inflation of relatively unimportant variables that appear in few models. As a simple indicator of model fit, we show the range of Nagelkerke's pseudo-R^2 for the models comprising the plausible set. (There is no accepted way to calculate a pseudo-R^2 for averaged models at present.)

Variance inflation factors (VIFs) were used to check for potential influence of multicollinearity on model results. Garden size and address density were found to have VIFs greater than 5, due to their high correlation (*rho* = -0.92; Table S1). We therefore re-ran models excluding garden size (all VIFS < 3). The results of the averaged models were very similar to those of the models including garden size (results not shown), so we do not consider collinearity to have influenced our results.

3. Results

The results of the averaged plausible set models (using orthogonally transformed data) are shown in Table 3. The marginal effects of each variable are plotted in Figure 1. These plots indicate the shape of the relationships between individual variables and obesity, and for interpretability are constructed from coefficients of averaged models using untransformed data; the results of the model using untransformed data are shown in the Supplementary Material, Table S2. When interpreting the marginal effects plots it is important to note the variable's distribution; this is indicated in the box-and-whisker plots below each plot.

3.1. Reception Year obesity

The averaged model fits the data well, with models in the plausible set having pseudo-R^2 values between 0.79 and 0.81. Only two greenspace variables appear in the final model for YR: tree density, which is highly statistically significant, with an association between higher densities of trees and lower rates of obesity; and play facility accessibility, which is not significant.

All three controlling variables are significant. Greater income deprivation, high levels of air pollution and lower address density are associated with higher rates of obesity. Income deprivation shows a curvilinear relationship: when income deprivation is low, increases are associated with increasing obesity rates; but when income deprivation is already high, further increases appear to be associated with lower obesity rates. However, across the numerical range where most of the data points lie, the relationship is positive (greater income deprivation = higher obesity rates), and given the small number of data points with very high deprivation levels the relationship in reality likely slows or saturates, i.e. further increases in deprivation are not related to obesity rates.

3.2. Year Six obesity

There is again a good fit between the models in the plausible set and the observed data (pseudo-R^2 = 0.87 for all models). Tree density is again statistically significant, with lower densities associated with higher rates of obesity. However, in this case the relationship is curvilinear. While increases in tree density are associated with lower obesity rates across the range where most of the data points lie, this saturates at low densities, i.e. further reductions in density are not associated with changes in obesity rates. Good greenspace accessibility is also significant, with better accessibility linearly associated with lower rates of obesity. Any greenspace accessibility, garden size and green cover appear in the plausible set, but do not approach statistical significance.

Greater income deprivation and lower address density are also associated with higher rates of obesity, showing similar relationships to those at YR. Air pollution is also approaching significance ($p = 0.061$). Income deprivation and air pollution show curvilinear relationships that saturate at the high ends of the numerical ranges, i.e. when income deprivation or air pollution is already high, further increases are not associated with changes in obesity rates.

4. Discussion

4.1. Associations between greenspace and childhood obesity

Our analysis found more and stronger relationships between controlling variables and obesity rates than between greenspace variables and obesity rates. The relationship with income deprivation is particularly strong. This is not surprising, as it is well known to have a large effect on population level health [31]. A number of other studies have found positive relationships between socioeconomic deprivation and childhood obesity in England and elsewhere [32–35]. Many of these studies found increasing obesity inequalities with deprivation with increasing age [33–35]. There are suggestions in our data that this is also the case in Sheffield: the marginal effect of income deprivation is greater across the range of deprivation where most LSOAs lie at Y6 than at YR (Figure 1h), and the differences in mean deprivation levels between LSOAs with the lowest and highest obesity rates are also greater at Y6 (Table 1).

Our measure of urbanicity is also significant at both ages, with lower rates of obesity at higher address densities even after accounting for income deprivation levels. The same relationship between childhood obesity and urbanicity has also been found in a study from Australia [32], as well as between population obesity and urbanicity in Montreal and the United States [36,37]. The direction of this relationship may arise from greater connectivity of destinations for children in more densely urbanised areas (e.g. friends' houses, parks) leading to higher levels of physical activity. Such neighbourhoods can also promote walking and cycling, with additional health benefits [38].

Air pollution is significantly associated with obesity rates at YR. The association is almost significant at Y6; the slightly weaker relationship at this age may arise from the greater mobility of older children leading to more opportunities for respite from high pollution levels. Our finding supports the body of evidence showing relationships between exposure to high levels of air pollution (PM_{10} and other pollutants) *in utero* and in early life and higher BMI throughout childhood [39,40]. Possible mechanisms for this effect are limitation of ability to be physically active e.g. due to asthma; direct physiological effects (e.g. endocrine disruption or mitochondria dysfunction) of pollutants, and the physiological and psychological consequences of inflammation caused by exposure [39,40].

After controlling for these socioeconomic and built environment factors, we find that higher tree density in the 100m radius around houses is associated with lower rates of obesity at both YR and Y6. Similar results have been observed in other cities. Zip codes in New York City with a greater density of street trees (within and in the 400m buffer around zip code boundaries) have lower rates of obesity in 3-5 year old children [25]. In inner-city Houston, Texas, 9-11 year old children with a greater area of trees and forest within 800m of their homes are also less likely to be obese [24]. This effect is likely to be mediated by higher levels of physical activity occurring in such areas [41]. Physical activity may be promoted by a more attractive environment for socialising and play [16,25], and also due to parents viewing such areas as safer for play and therefore permitting more independent outdoor activity [25]. However, there may also be residual confounding related to socioeconomic status, as more affluent residential areas often have greater tree cover [19,42] and lower levels of air pollution [43]. Diet quality (including amongst children), which contributes to obesity prevention, is also associated with socioeconomic status due to financial and time barriers [44].

Additionally at Y6, high rates of access to a good quality greenspace within 300m from home are associated with lower rates of obesity. The accessibility of parks and playgrounds is found to be related to rates of obesity amongst children and adolescents [45,46]. A longitudinal study following children from age 9-10 to 18 also found that a greater area of parks within

500m of homes was associated with less of an increase in BMI, especially for boys [47]. This is not always the case, however [25], and may in some cases be influenced by factors such as ethnicity; for example, Alexander et al. [46] found that Non-Hispanic Black children but not Non-Hispanic White children in the US had lower rates of obesity in areas with access to a park.

It has been postulated that where no relationship between park access and obesity is observed, this is due to reliance on car transportation instead of walking/cycling, meaning that children are not dependent on park resources so close to home [48]. Another study from the UK also found no relationship between obesity rates and park access at YR [48]. The authors suggest that children of this age in the UK predominantly play elsewhere, such as in private gardens [48].

Some studies have shown that access to a park is associated with higher levels of physical activity [49]. It is not always clear that physical activity is necessarily the causal mechanism reducing obesity rates, however. A mediation analysis in a US-wide study of 40,000 children did not find evidence to support the hypothesis that physical activity mediates the relationship between park access and obesity [46].

In our study, rates of access to *any* greenspace do not show any relationship to obesity, suggesting that children have quality-related requirements of greenspaces in order either to use them or to obtain health benefits from their use. One explanation for this would be that larger parks may be more likely to include playgrounds and other play facilities, which promote physical activity; however, play facilities accessibility was not significant for either age group, suggesting that presence of play facilities alone is inadequate to explain health benefits. Larger parks may also include a variety of landscape features (e.g. trees and other plants, water features) that are preferred by children and promote physical activity [50]. Children's requirements may vary by demographic group: for example, physical activity in parks amongst girls in the US was promoted by paths and running tracks, playgrounds, basketball courts and good lighting [16]. Conversely, the presence of skateboard parks reduced physical activity levels amongst these girls [16]. Interestingly, a study of adults in Rotherham – a town adjacent to Sheffield – found that neither park access nor quality was related to adult obesity [51], again highlighting the importance of considering children's needs separately to those of adults.

4.2. Limitations

A major limitation of cross-sectional studies is that causality cannot be inferred. Observed relationships may be due to reverse causation or residual confounding. This is a problem in many studies of the relationship between greenspace and health, as they are primarily observational and therefore cannot provide strong evidence for causation, especially where relationships are complex [52].

We chose LSOAs as our spatial unit of analysis. While LSOA boundaries are drawn to be socially homogeneous, the average LSOA population is 1600, making socioeconomic and demographic variation inevitable. Analyses of LSOAs may therefore be subject to the ecological fallacy, where population-level associations do not hold at individual-level [53].

Similarly, analysis at alternative levels or areas of aggregation may not find the same results [53]. A particularly relevant point to note is that any spatial aggregation unit is unlikely to capture the spatial environment experienced by residents on a day to day basis [54]. We have attempted to address this issue by designing indicators at different scales, e.g. some aggregated to LSOA boundaries and others calculated on the environment around individual houses.

There are nevertheless some limitations associated with our greenspace indicators. We were only able to capture the greenspace that is present in the environment, and not its use, which is likely to provide the majority of health benefits [52]. Data on greenspace usage is rarely available, and costly to collect at the scales required for epidemiological studies. Our selected indicators may have failed to capture the aspects of greenspace that are most relevant for health. Also, we have not tested for interactions between indicators (doing so would have proved computationally unfeasible using our multi-model inference approach); this is important as, for example, socioeconomic status can alter the relationship between availability of resources for physical activity and obesity [55].

Further limitations of the greenspace indicators are that the accessibility indicators only capture greenspaces up to 300m from homes. While greenspace use tends to fall rapidly with distance from home [56], it is implausible that there is no use of greenspaces more than 300m from home. Also, the green cover and accessibility indicators treat all greenspace as a single category, while it is likely that certain greenspaces have a greater influence on obesity rates than others. Garden size and tree density do capture two types of greenspace that we considered particularly likely to be important, but it is possible that other types have strong influences as well. Additionally, the accessibility indicators only include greenspaces identified as part of Sheffield's green and open spaces assessment.

A final limitation is that we were unable to stratify our analysis by demographic factors such as gender or ethnic background. Previous studies have found that both of these factors influence the relationship between greenspace and physical activity/obesity [46,47].

4.3. Conclusions

Using a small-area population analysis, we have found a relationship between lower obesity rates amongst children in Reception Year (ages 4-5) and Year Six (ages 10-11) and higher density of trees in a 100m buffer around homes, after controlling for several socioeconomic and built environment factors. This indicates that the greenspace environment immediately around young children's homes has an impact on their chance of becoming obese. In Year Six, obesity rates are lower where more homes have access within 300m (approximately a five-minute walk) of a greenspace that is large, natural-feeling and of high quality, suggesting that older children also benefit from suitable greenspace resources located slightly further from home. It seems likely that these associations are due to the promotion by greenspace of physical activity, and that the absence of a relationship between access to parks amongst younger children is due to reliance on other areas, such as private gardens, for active play – although we did not find garden *size* to be a significant predictor of obesity.

Given the importance of childhood obesity as a public health issue, we recommend that attention be given to the local greenspace environment when considering interventions or planning new residential areas. Specifically, we recommend that high-quality greenspace be provided both in the immediate surroundings of housing, as well as slightly further afield. Greenspaces near to homes could, for example, be provided by designing residential streets around central greens with a variety of planting, including trees. Local parks should also be provided, with consideration to the specific needs of children in terms of quality and accessibility. While not understating the primary importance of alleviating deprivation for reducing the prevalence of obesity, ensuring that children have access to age-appropriate greenspace resources could make an important contribution to reducing childhood obesity.

References

1. Ziauddeen N, Roderick PJ, Macklon NS, Alwan NA. Predicting childhood overweight and obesity using maternal and early life risk factors: a systematic review. *Obes Rev*. 2018;19(3):302-312. doi:10.1111/obr.12640

2. Mihrshahi S, Baur LA. What exposures in early life are risk factors for childhood obesity? *J Paediatr Child Health*. 2018;54(12):1294-1298. doi:10.1111/jpc.14195

3. Sahoo K, Sahoo B, Choudhury A, Sufi N, Kumar R, Bhadoria AS. Childhood obesity: Causes and consequences. *J Fam Med Prim Care*. 2015;4(2):187. doi:10.4103/2249-4863.154628

4. Mihrshahi S, Gow ML, Baur LA. Contemporary approaches to the prevention and management of paediatric obesity: an Australian focus. *Med J Aust*. 2018;6:267-274. doi:10.5694/mja18.00140

5. Woo Baidal JA, Locks LM, Cheng ER, Blake-Lamb TL, Perkins ME, Taveras EM. Risk Factors for Childhood Obesity in the First 1,000 Days: A Systematic Review. *Am J Prev Med*. 2016;50(6):761-779. doi:10.1016/j.amepre.2015.11.012

6. Miller AL, Lumeng JC. Pathways of Association from Stress to Obesity in Early Childhood. *Obesity*. 2018;26(7):1117-1124. doi:10.1002/oby.22155

7. Vanaken GJ, Danckaerts M. Impact of green space exposure on children’s and adolescents’ mental health: A systematic review. *Int J Environ Res Public Health*. 2018;15(12):2668. doi:10.3390/ijerph15122668

8. McCurdy LE, Winterbottom KE, Mehta SS, Roberts JR. Using nature and outdoor activity to improve children’s health. *Curr Probl Pediatr Adolesc Health Care*. 2010;40(5):102-117. doi:10.1016/j.cppeds.2010.02.003

9. Kepper MM, Staiano AE, Katzmarzyk PT, et al. Neighborhood Influences on Women’s Parenting Practices for Adolescents’ Outdoor Play: A Qualitative Study. *Int J Environ Res Public Health*. 2019;16(20):3853. doi:10.3390/ijerph16203853

10. Evans GW, Jones-Rounds ML, Belojevic G, Vermeylen F. Family income and childhood obesity in eight European cities: The mediating roles of Neighborhood characteristics and physical activity. *Soc Sci Med*. 2012;75(3):477-481. doi:10.1016/j.socscimed.2012.03.037

11. Schalkwijk AAH, Van Der Zwaard BC, Nijpels G, Elders PJM, Platt L. The impact of greenspace and condition of the neighbourhood on child overweight. *Eur J Public Health*. 2018;28(1):88-94. doi:10.1093/eurpub/ckx037

12. Petraviciene I, Grazuleviciene R, Andrusaityte S, Dedele A, Nieuwenhuijsen MJ. Impact of the social and natural environment on preschool-age children weight. *Int J Environ Res Public Health*. 2018;15(3):449. doi:10.3390/ijerph15030449

13. Brindley P, Cameron R, Ersoy E, Jorgensen A, Maheswaran R. Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. *Urban For Urban Green*. 2019;39:45-54. doi:10.1016/j.ufug.2019.01.015

14. Wheeler BW, Lovell R, Higgins SL, et al. Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *Int J Health Geogr*. 2015;14(1):17. doi:10.1186/s12942-015-0009-5

15. Day R, Wager F. Parks, streets and “just empty space”: The local environmental experiences of children and young people in a Scottish study. *Local Environ*. 2010;15(6):509-523. doi:10.1080/13549839.2010.487524

16. Cohen DA, Ashwood JS, Scott MM, et al. Public Parks and Physical Activity Among Adolescent Girls. *Pediatrics*. 2006;118(5):e1381-e1389. doi:10.1542/peds.2006-1226

17. Veitch J, Salmon J, Ball K. Children’s active free play in local neighborhoods: A behavioral mapping study. *Health Educ Res*. 2008;23(5):870-879. doi:10.1093/her/cym074

18. Hand KL, Freeman C, Seddon PJ, Recio MR, Stein A, van Heezik Y. Restricted home ranges reduce children’s opportunities to connect to nature: Demographic, environmental and parental influences. *Landsc Urban Plan*. 2018;172(March 2017):69-77. doi:10.1016/j.landurbplan.2017.12.004

19. Mitchell R, Popham F. Effect of exposure to natural environment on health inequalities: an observational population study. *Lancet*. 2008;372(9650):1655-1660. doi:10.1016/S0140-6736(08)61689-X

20. Mears M, Brindley P, Maheswaran R, Jorgensen A. Understanding the socioeconomic equity of publicly accessible greenspace distribution: The example of Sheffield, UK. *Geoforum*. 2019;103:126-137. doi:10.1016/j.geoforum.2019.04.016

21. Cole TJ, Freeman JV, Preece MA. Body Mass Index reference curves for the UK, 1990. *Ann Dis Child*. 1995;73:25-29. doi:10.1136/adc.73.1.25

22. Public Health England. *National Child Measurement Programme: Operational Guidance 2019*. London; 2019. www.gov.uk/phe%5Cnhttps://www.gov.uk/government/uploads/system/uploads/attachment_data/file/377902/NCMP_operational_guidance.pdf.

23. Lachowycz K, Jones AP, Page AS, Wheeler BW, Cooper AR. What can global positioning systems tell us about the contribution of different types of urban greenspace to children’s physical activity ? *Health Place*. 2012;18(3):586-594. doi:10.1016/j.healthplace.2012.01.006

24. Kim J-H, Lee C, Olvera NE, Ellis CD. The Role of Landscape Spatial Patterns on Obesity in Hispanic Children Residing in Inner-City Neighborhoods. *J Phys Act Heal*. 2014;11(8):1449-1457. doi:10.1123/jpah.2012-0503

25. Lovasi GS, Schwartz-Soicher O, Quinn JW, et al. Neighborhood safety and green space as predictors of obesity among preschool children from low-income families in New York City. *Prev Med (Baltim)*. 2013;57(3):189-193. doi:10.1016/j.ypmed.2013.05.012

26. Gehl J. *Cities for People*. Washington D.C.: Island Press; 2010.

27. Van Den Bosch MA, Egorov AI, Mudu P, et al. Development of an urban green space indicator and the public health rationale. *Scand J Public Health*. 2016;44(2):159-167. doi:10.1177/1403494815615444

28. Richardson E, Pearce J, Mitchell R, Day P, Kingham S. The association between green space and cause-specific mortality in urban New Zealand: an ecological analysis of green space utility. *BMC Public Health*. 2010;10:240. doi:https://doi.org/10.1186/1471-2458-10-240

29. Symonds MRE, Moussalli A. A brief guide to model selection, multimodel inference and model averaging in behavioural ecology using Akaike's information criterion. *Behav Ecol Sociobiol*. 2011;65(1):13-21. doi:10.1007/s00265-010-1037-6

30. Richards SA, Whittingham MJ, Stephens PA. Model selection and model averaging in behavioural ecology: The utility of the IT-AIC framework. *Behav Ecol Sociobiol*. 2011;65(1):77-89. doi:10.1007/s00265-010-1035-8

31. Reijneveld SA, Verheij RA, De Bakker DH. The impact of area deprivation on differences in health: Does the choice of the geographical classification matter? *J Epidemiol Community Health*. 2000;54(4):306-313. doi:10.1136/jech.54.4.306

32. Gibb S, Shackleton N, Audas R, et al. Child obesity prevalence across communities in New Zealand: 2010–2016. *Aust N Z J Public Health*. 2019;43(2):176-181. doi:10.1111/1753-6405.12881

33. Kinra S, Nelder RP, Lewendon GJ. Deprivation and childhood obesity: A cross sectional study of 20,973 children in Plymouth, United Kingdom. *J Epidemiol Community Health*. 2000;54(6):456-460. doi:10.1136/jech.54.6.456

34. Nau C, Schwartz BS, Bandeen-Roche K, et al. Community socioeconomic deprivation and obesity trajectories in children using electronic health records. *Obesity*. 2015;23(1):207-212. doi:10.1002/oby.20903

35. White J, Rehkopf D, Mortensen LH. Trends in socioeconomic inequalities in body mass index, underweight and obesity among English children, 2007-2008 to 2011-2012. *PLoS One*. 2016;11(1):e0147614. doi:10.1371/journal.pone.0147614

36. Van Hulst A, Gauvin L, Kestens Y, Barnett TA. Neighborhood built and social environment characteristics: A multilevel analysis of associations with obesity among children and their parents. *Int J Obes*. 2013;37(10):1328-1335. doi:10.1038/ijo.2013.81

37. Xu Y, Wang F. Built environment and obesity by urbanicity in the U.S. *Heal Place*.

2015;34:19-29. doi:10.1016/j.healthplace.2015.03.010

38. Seaman PJ, Jones R, Ellaway A. It's not just about the park, it's about integration too: Why people choose to use or not use urban greenspaces. *Int J Behav Nutr Phys Act*. 2010;7:78. doi:10.1186/1479-5868-7-78

39. Lichtveld K, Thomas K, Tulve NS. Chemical and non-chemical stressors affecting childhood obesity: A systematic scoping review. *J Expo Sci Environ Epidemiol*. 2018;28(1):1-12. doi:10.1038/jes.2017.18

40. McConnell R, Gilliland FD, Goran M, Allayee H, Hricko A, Mittelman S. Does near-roadway air pollution contribute to childhood obesity? *Pediatr Obes*. 2016;11(1):1-3. doi:10.1111/ijpo.12016

41. Lovasi GS, Jacobson JS, Quinn JW, Neckerman KM, Ashby-Thompson MN, Rundle A. Is the environment near home and school associated with physical activity and adiposity of urban preschool children? *J Urban Heal*. 2011;88(6):1143-1157. doi:10.1007/s11524-011-9604-3

42. Landry SM, Chakraborty J. Street trees and equity: Evaluating the spatial distribution of an urban amenity. *Environ Plan A*. 2009;41(11):2651-2670. doi:10.1068/a41236

43. Science for Environment Policy. *Links between Noise and Air Pollution and Socioeconomic Status. In-Depth Report 13 Produced for the European Commission*. UWE, Bristol; 2016. doi:10.2779/200217

44. Wolfson JA, Ramsing R, Richardson CR, Palmer A. Barriers to healthy food access: Associations with household income and cooking behavior. *Prev Med Reports*. 2019;13(December 2018):298-305. doi:10.1016/j.pmedr.2019.01.023

45. Veugelers P, Sithole F, Zhang S, Muhajarine N. Neighborhood characteristics in relation to diet, physical activity and overweight of Canadian children. *Int J Pediatr Obes*. 2008;3(3):152-159. doi:10.1080/17477160801970278

46. Alexander DS, Huber LRB, Piper CR, Tanner AE. The association between recreational parks, facilities and childhood obesity: A cross-sectional study of the 2007 National Survey of Children's Health. *J Epidemiol Community Health*. 2013;67(5):427-431. doi:10.1136/jech-2012-201301

47. Wolch J, Jerrett M, Reynolds K, et al. Childhood obesity and proximity to urban parks and recreational resources: A longitudinal cohort study. *Heal Place*. 2011;17(1):207-214. doi:10.1016/j.healthplace.2010.10.001

48. Poole R, Moon G. What is the association between healthy weight in 4–5-year-old children and spatial access to purposefully constructed play areas? *Heal Place*. 2017;46(May):101-106. doi:10.1016/j.healthplace.2017.05.012

49. Roemmich JN, Epstein LH, Raja S, Yin L, Robinson J, Winiewicz D. Association of access to parks and recreational facilities with the physical activity of young children. *Prev Med (Baltim)*. 2006;43(6):437-441. doi:10.1016/j.ypmed.2006.07.007

50. Li C, Seymour M. Children's perceptions of neighbourhood environments for walking and outdoor play. *Landsc Res*. 2019;44(4):430-443.

doi:10.1080/01426397.2018.1460336

51. Hobbs M, Green MA, Griffiths C, et al. Access and quality of parks and associations with obesity: A cross-sectional study. *SSM - Popul Heal*. 2017;3(July):722-729. doi:10.1016/j.ssmph.2017.07.007

52. Lee ACK, Maheswaran R. The health benefits of urban green spaces: a review of the evidence. *J Public Health (Bangkok)*. 2011;33(2):212-222. doi:10.1093/pubmed/fdq068

53. Weigand M, Wurm M, Dech S, Taubenböck H. Remote Sensing in Environmental Justice Research—A Review. *ISPRS Int J Geo-Information*. 2019;8(1):20. doi:10.3390/ijgi8010020

54. Kwan MP. The Uncertain Geographic Context Problem. *Ann Assoc Am Geogr*. 2012;102(5):958-968. doi:10.1080/00045608.2012.687349

55. Hobbs M, Griffiths C, Green MA, Jordan H, Saunders J, McKenna J. Associations between the combined physical activity environment, socioeconomic status, and obesity: a cross-sectional study. *Perspect Public Health*. 2018;138(3):169-172. doi:10.1177/1757913917748353

56. Schipperijn J, Ekholm O, Stigsdotter UK, et al. Factors influencing the use of green space: Results from a Danish national representative survey. *Landsc Urban Plan*. 2010;95(3):130-137. doi:10.1016/j.landurbplan.2009.12.010

Tables and figure legends

Table 1. Demographic statistics of Sheffield LSOAs divided into tertiles of obesity (ratio of observed to expected rates) at Reception Year and Years Six. Tertile 1 = lowest obesity ratio. ICADI = Income Deprivation Affecting Children Index; measures proportion of children living in income deprived families. All data from 2011 census.

Variable	**Reception Year**			**Year Six**		
	1	**2**	**3**	**1**	**2**	**3**
Index of Multiple Deprivation						
Mean	15.94	28.85	37.59	13.56	27.90	41.04
SD	13.65	18.48	19.83	11.69	17.52	18.31
IDACI						
Mean	0.11	0.22	0.28	0.09	0.22	0.31
SD	0.11	0.15	0.16	0.08	0.15	0.15
Population						
Mean	1622.29	1597.92	1563.38	1549.39	1581.64	1652.70
SD	303.07	248.34	223.27	180.95	243.85	327.87
Child population (0-15 years)						
Mean	266.78	307.16	302.61	234.84	287.24	354.75
SD	99.30	120.00	110.31	88.56	87.70	120.41
Mean % of population	16.66	19.03	19.33	15.26	18.19	21.59
Children in poor health						
Mean	1.72	2.40	3.03	2.24	2.30	2.61
SD	2.50	2.09	2.86	2.25	2.68	2.72
Mean % of children	0.58	0.76	0.98	0.78	0.71	0.82
Mean ethnic composition (%)						
White	76.95	73.02	76.65	80.87	76.70	69.05
Mixed/multiple ethnic group	5.80	5.97	6.28	5.65	5.61	6.79
Asian/Asian British	10.32	11.46	7.70	7.32	9.62	12.54
Black/African/Caribbean/Black British	3.70	5.25	5.88	2.59	5.11	7.16
Other ethnic group	3.22	4.30	3.49	3.57	2.97	4.46

Table 2. Descriptive statistics of greenspace metrics.

Variable	Min	Q1	Median	Q3	Max	Range	Mean	St. Dev.
Income deprivation	0.01	0.06	0.13	0.29	0.55	0.55	0.17	0.13
Air pollution	13.00	14.90	15.70	16.40	19.80	6.82	15.70	1.20
Address density	30.90	74.40	89.50	116.00	415.00	384.00	104.00	52.30
Green cover	0.01	0.16	0.28	0.48	0.98	0.98	0.34	0.22
Tree density	12.80	78.00	99.90	129.00	223.00	211.00	105.00	38.90
Garden size	0.73	110.00	175.00	217.00	768.00	767.00	178.00	106.00
Any greenspace accessibility	0.04	0.57	0.81	0.95	1.00	0.97	0.74	0.25
Good greenspace accessibility	0.00	0.00	0.06	0.37	1.00	1.00	0.20	0.27
Play facility accessibility	0.00	0.00	0.20	0.45	1.00	1.00	0.26	0.26

Table 3. Averaged models for rates of obesity at Reception Year and Year Six in Sheffield LSOAs. Empty lines indicate that the variable did not appear in the plausible set (quadratic terms that did not appear in any plausible set are not shown). Significant terms are shown in bold.

	Reception Year					**Year Six**				
	Estimate	**SE (adj.)**	**z value**	**p value**		**Estimate**	**SE (adj.)**	**z value**	**p value**	
(Intercept)	**0.314**	**0.016**	**20.119**	**<0.001**	**	**-0.069**	**0.013**	**5.351**	**<0.001**	***
Income deprivation	**1.889**	**0.327**	**5.787**	**<0.001**	***	**3.101**	**0.295**	**10.528**	**<0.001**	***
Income deprivation ^2	**-1.721**	**0.278**	**6.198**	**<0.001**	***	**-1.026**	**0.227**	**4.510**	**<0.001**	***
Air pollution	**0.889**	**0.330**	**2.689**	**0.007**	**	0.593	0.317	1.871	0.061	
Air pollution ^2						-0.234	0.289	0.809	0.419	
Address density	**-2.432**	**0.434**	**5.602**	**<0.001**	***	**-1.298**	**0.596**	**2.178**	**0.029**	*
Green cover						0.327	0.328	0.996	0.319	
Tree density	**-1.070**	**0.363**	**2.951**	**0.003**	**	**-0.862**	**0.325**	**2.655**	**0.008**	**
Tree density ^2	0.000	0.000	0.000	1.000		-0.453	0.376	1.207	0.227	
Garden size						-0.550	0.574	0.958	0.338	
Any greenspace accessibility						0.021	0.108	0.196	0.845	
Good greenspace accessibility						**-0.565**	**0.269**	**2.098**	**0.036**	*
Play facility accessibility	0.004	0.106	0.038	0.970						
Play facility accessibility ^2	-0.027	0.122	0.221	0.825						

Figure 1. Marginal effects of greenspace and controlling variables on obesity at Reception Year (dashed lines) and Year Six (solid lines) in Sheffield LSOAs. Marginal effects are shown on log scale (as per negative binomial GML link function). Missing lines indicate the variable did not appear in the plausible set for the age. Box and whisker plots indicate variable distribution, with the box encompassing the interquartile range and whiskers indicating a further 1.5x the interquartile range. Units: (a) proportion cover, (b) count of trees within 100m of addresses, (c) m^2, (d-f) proportion of addresses with access, (g) index, (h) $\mu g\ m^{-2}$, (i) count of addresses within 100m of addresses.