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RESEARCH ARTICLE

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Road traffic modifies green space and self-rated health associations across urban England and Wales

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ABSTRACT

Urban green space is increasingly linked to better public health. Natural environments in parks and woodlands may promote physical activity and prosocial behaviour, reduce stress, and restore cognition, yet modifiers of these benefits are poorly understood. Road traffic may reduce a sense of "being away" and deter activity, potentially limiting health gains. We tested whether traffic modifies green space–health associations using a novel exposure metric based on green space visibility from footpaths. In a cross-sectional ecological study of Census output areas within built-up urban areas in England, and we related the prevalence of self-rated positive (good/very good) health (2011 Census) to "experienceable" green space visible from footpaths with and without adjacent traffic. Non-linear spline models adjusted for age, sex, and area-level confounders showed strong positive associations for trees outside woodland visible from roadside footpaths with traffic and for woodland visible from footpaths without traffic. Associations for ground cover adjacent to footpaths were generally positive but smaller. By contrast, woodland adjacent to footpaths with traffic showed a negative association. The findings support provision of woodland experiences away from traffic while also suggesting benefits of roadside tree planting.

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Greenspace; ecosystem services; visibility analysis

Introduction

Cities harbour a wide variety of natural and semi-natural green spaces such as parks, gardens, woodlands, street trees, and open fields. Recent systematic reviews have established that more green space near to where people live is associated with improved health across most health indicators studied (Banwell et al. 2024), for example, all-cause mortality (Rojas-Rueda et al. 2019; Zhou et al. 2024), physical activity engagement, risk of myocardial infarction (Poulsen et al. 2024), and improved mood (Kondo et al. 2018). These benefits may potentially also be economically substantial. In the UK, for example, the avoided cost to the National Health Service from green spaces was estimated at £2.4 billion annually (Eftec 2017). The role of green spaces in improving public health is also increasingly being recognised by health care providers, policymakers, urban planners, designers and architects (Millennium Ecosystem Assessment 2005). The World Health Organization (WHO) has identified protecting and creating green spaces in urban areas (WHO Regional Office for Europe 2017) as part of the solution to tackle the global rise in non-communicable diseases, which account for ~88% of European deaths (WHO Regional Office for Europe 2016).

Several pathways linking sensory experiences of green space (such as sight, sound, and smell) to health have been proposed in the literature, including reduced stress (Corazon et al. 2019), restored cognitive fatigue (Stevenson et al. 2018) and making physical activity more attractive (Silva et al. 2018). Being closer to

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green space in urban environments also decreases sun exposure and the effect of urban heat islands, which improves thermal comfort, and wellbeing (Richards et al. 2022).

In the absence of personal activity data, many studies use the of sensory experiences near to where people live (e.g. within their walkable neighbourhood) as an indicator of actual green space sensory experiences a person has. Using this metric is assumed that people are more likely to have a sensory experience of green space if it's near to home, either incidentally on their walk around their neighbourhood, or intentionally, as local green space requires less effort to visit than distance green space. A potential experience is often equated to the sum of green space cover. However, more nuanced approaches exist to define green space. One example, is the proportion of vegetation derived from segmented street view photos at set intervals alongside roads (Helbich et al. 2021; Ma et al. 2025). However, street view photos rarely cover footpaths away from roads, which are amongst the most common points of nature exposure when walking (e.g. parks, woodlands, pedestrianised streets) and can be computationally intensive for country scale analyses. Another approach is calculating the area of green space within a set buffer distance from roads/ footpaths near to home (Carthy et al. 2020), which is less computationally intensive. These can be improved by summing the area of green space under isovists, which exclude any views of green space obstructed by buildings, along the same roads/footpaths (Benedikt 1979).

In addition to those already studied, many other factors may modify associations between exposure to green space and health (Marselle et al. 2021) including experiencing green space simultaneously with road traffic, something rarely investigated (Dopico et al. 2026). The modifying effect of green space and health associations may differ by vegetation type. This is due to these different spaces' links to health working across different pathways. For example, road traffic can be a visual or audible distraction, which may reduce the sense of "being away" from urban areas and diminish stress-reduction (Ulrich 1983) and cognitive restoration (Kaplan 1995), which may be more important in environments where people look for stress reduction, such as natural biodiverse woodlands. Conversely, the presence of street trees next to a trafficked road, may make walking more appealing. This has been the mediator proposed to be activated in studies finding associations between neighbourhood green space and increases in physical activity and physical health (Barnett et al. 2017; Tsai et al. 2019b). Different types of green space have also found to impact different health indicators quantitatively, suggesting that greenspace-health pathway activation potential varies by green space type. For example, living in an area with more shrubland and grass-herb vegetation was found to decrease the probability of having a mental health disorder in Canada, while no association was found with self-rated health for any green space type (Jarvis et al. 2020). Woodland was associated with positive mental health, but no association was found with any green space type and general health in Washington State USA (Akpinar et al. 2016).

Should traffic reduce or enhance the benefits of green space it may be a deciding factor in cost-benefit analyses on what type of green space to develop or conserve in a specific location. For example, it may support or undermine tree planting schemes that either provide dense wooded or sparse canopies near roads, for example, the recently proposed £3.1 million London scheme (Mayor of London Office 2022). This is especially relevant given the high inequalities in road-traffic noise within parks in many cities, e.g. London (Adams et al. 2025). Furthermore, it can help guide practitioners whether individuals should visit a green space with or without traffic when prescribing green space visits (Robinson et al. 2020). Green space benefits are often generalised by green cover types (e.g. woodland, grassland, street trees), including in health studies (Alcock et al. 2015; Akpinar et al. 2016; Picavet et al. 2016; Tsai et al. 2019a, 2019b; Jarvis et al. 2020) making it valuable to align our analyses by doing the same. Planners can consider how associations differ by traffic alongside other factors, for example, the different cooling potential of green cover types (Richards et al. 2020), or the variety of ecosystem service quantities provided by woodland (Burton et al. 2018) and the often different management requirements of distinct green cover types. Despite this need there is a limited evidence on how the association between residential green space exposure and health is influenced by road-side traffic.

Here, we present a cross-sectional small-area ecological study, across urban Census Output Areas (COAs) in England and Wales. We investigate (i) the direction, shape, magnitude, and uncertainty of associations of green space visible from footpaths with self-rated positive health and (ii) whether the association is consistent across different types of green space, including ground cover, woodland, and tree outside woodland; and (iii) whether association differs when green space was experienced from a footpath with adjacent traffic (e.g. a sidewalk or footway) compared to a footpath without adjacent traffic (e.g. a woodland path).

Materials and methods

We included all COAs in England and Wales classified as built-up (urban) by the Office for National Statistics (ONS) built-up area classification (Office for National Statistics 2013), according to the 2011 census. COAs are the smallest census dissemination unit in the United Kingdom, and urban COAs have an average population of 311 residents. There are 146,970 built-up (urban) COAs in England and Wales, which according to the 2011 census contained 45.7 million people, 81% of the population in England and Wales. We used COAs as the geographical unit of analysis as their high spatial resolution allows for a more precise prediction of the accessibility of green spaces from a person's dwelling than coarser geographies, and consequently increases exposure contrast across geographic units. Furthermore, COAs are designed to contain socially similar residents, based on dwelling type and household tenureship.

Our outcome variable was the proportion of COA residents with self-rated very good or good (positive) health, according to the 2011 census. Census respondents were given five options to answer the question "how is your health in general? (very good, good, fair, bad, very bad)". We used positive self-rated health as it is representative of multiple aspects of an individual's physical and mental health (Simon et al. 2005) and individuals' perceptions of their health. Furthermore, self-rated health has been previously used in studies measuring health benefits from natural environments, making results comparable to other studies (Maas et al. 2006; Wheeler et al. 2015; Brindley et al. 2018).

We used the age and sex adjusted ratio of COA residents with positive self-rated health as a proportion of all COA residents as the dependent variable in all our models. This adjustment was done by directly standardising the proportion of residents in each COA with self-rated positive health to the average age and sex structure of all COAs in England and Wales using the package (Kumar 2019) in R (R Core Team 2019).

We differentiated green spaces into four types based on their physical vegetation characteristics: i) , ii) , iii) and iv) all three types of green space aggregated together, herein referred to as (Table 1).

We fused two remote sensing products to capture a high diversity of green spaces in urban areas. These were the Land Cover Map 2017 (LCM2017) from the Centre for Ecology and Hydrology (Morton et al. 2020) and

Categorisation of green spaces into green cover types.

Green cover		Description	Data source and definition
All green cover	Woodland	Trees in clusters not mixed with non-vegetated surfaces. This includes stands of trees in parks and large woodland areas	Land in the Centre for Ecology and Hydrology Land Cover Map 2017 classed as deciduous woodland or coniferous woodland
	Tree outside woodland	Smaller patches of trees that may be interwoven with non-vegetated areas.	Land not *woodland* (see above) with a tree cover density of more than 50% in the Copernicus Tree Cover Density Product
	Ground cover	Low laying patches of vegetation including agricultural land and managed grassland	Areas that are not *tree outside woodland* (see above) and classed in the Land Cover Map 2017 as either: arable, improved grassland, neutral grassland, calcareous grassland, acid grassland, fen, heather, heather grassland, bog or saltmarsh

the Copernicus Land Monitoring service Tree Cover Density product (herein referred to as Copernicus TCD) (European Environment Agency, 2018), both of which have a 20 m × 20 m resolution. The LCM2017 is created by classifying remotely sensed land cover hyperspectral imagery and ancillary data into 21 land cover classes (based on the United Kingdom Biodiversity Action Plan habitat descriptions), using a random forest classifier trained on the spectral signature of said classes as ground truth (Morton et al. 2011). The Copernicus TCD was created by classifying Sentinel 2A and Landsat 8 satellite imagery using a support vector machine classifier trained on manually indicated tree cover proportions per 20 m × 20 m grid cell from higher resolution (e.g. SPOT-5 2.5 m × 2.5 m) data.

The LCM2017 has 12 detailed land cover classes relating to green space. We combined classes and to and the remaining ten classes including different types of arable land and grassland to (Table 1). We defined grid cells that are not classified as but have more than 50% tree cover based on Copernicus TCD as (Table 1). This analysis was completed using the package (Hijmans et al. 2019) in R. represents closed or near closed tree canopies, rather than individual trees. is tree cover outside the above definition and includes individual trees over . is low laying vegetation including grassland (Table 1).

To identify green cover experienceable from footpaths for each COA, we followed a three-step process (see Figure 1). First, we identified footpaths that were available from each COA Population Density-Weighted

Panel A: study area extent including all built-up (urban) census output areas (COAs) in England and Wales. *panel B*: distribution of population density-Weighted centroids (PDWC) for all COAs in Worthing borough Council. *panel C*: 1 km circular buffer from PDWC of Findon Valley COA used to identify available footpaths. *panel D*: experienceable natural environments from every footpath within 1 km of PDWC, restricted to ~100 m from footpaths, overlaid with green cover type. *panel E*: experienceable area from footpaths with adjacent traffic. Panel F: experienceable area from footpaths with no adjacent traffic.

Centroid (PDWC). Second, we differentiated between those adjacent to traffic and those without adjacent traffic. Third, we extracted the areal coverage of green cover that was experienceable from each type of our three footpath types.

We identified footpaths using the Ordnance Survey (OS) Mastermap Highways Network: Road and Path products (Ordnance Survey 2017), which is the most accurate path network information across Great Britain (Ordnance Survey 2020a, 2020b). We defined available footpaths as within a 1,000 m radius from a COA PDWC (see Figure 1(C)). Rather than the COA geometric centroid, we used the COA PDWCs, i.e. the point location with the shortest distance to all residential postcodes (representing on average of 12 households) within a COA, because these are a better approximation of where people live within a COA. A 1,000 m radius (representing approximately a 15-minute walk) was chosen as it is comparable to the range (300 m to 1.6 km) used in previous research linking natural environment and health (van den Berg et al. 2015; Kondo et al. 2018) and it is the same radius used in many previous studies (de Vries et al. 2003; Bell et al. 2008; Maas et al. 2009; Wolch et al. 2011; Astell-Burt et al. 2013).

We defined footpaths adjacent to traffic ( ) as any road or path, except those that are illegal to walk on (i.e. motorways and slip roads), shared-use carriageways (as these are principally for use by pedestrians, as defined by OS) and those with little or no traffic (i.e. tracks, closed roads, roads under construction, roads that had access restrictions for motor vehicles, or a "no entry" sign) (Ordnance Survey 2017). We defined footpaths which are not adjacent to traffic ( ) as any path in the product, or any road that was either a shared use carriageway, or a track or road that had access restrictions for motor vehicles (Ordnance Survey 2017). We processed this data using R packages and (Dowle et al. 2019; Wickham et al. 2019).

We defined experienceable green cover as green cover that is visible from a footpath. As such, we first identified the visible area from available footpaths for each COA and then overlaid these with the green cover types (see Figure 1(D)).

To identify the visible area from an available footpath, we started by generating viewpoints, regularly spaced points (every 50 m or at the centre of paths/roads < 50 m long) along each available footpath. The visible area from these points, was the two-dimensional field of view, unobstructed by buildings, calculated from isovists (Weitkamp et al. 2014). We created and implemented our own isovists in R using a raycasting algorithm to create the visible area (see Appendix A for details). We restricted the view distance to a maximum of 100 m for and 100 m plus the road width for . Our building footprints came from the OS Vectormap product, which includes buildings with a footprint over 50 m^2 (Ordnance Survey 2018).

We then combined the visible areas across all viewpoints for and , within each COA. Figure 1(D-F) show examples of one COA's visible green cover from available and , respectively. The isovist function we used can be accessed here: https://rpubs.com/richardneilbelcher/isovist. All other operations were performed in R using the packages , , and (Dowle et al. 2019; Pebesma et al. 2019; Wickham et al. 2019).

We then computed the total area (in km^2) covered by each of the four green cover types (, , and within each of the three experienceable areas from , and , therefore, creating 12 green space-footpath combinations (Table 2). For this purpose, all grid cells whose geometric centroid intersected the experienceable area were extracted using R package (Hunziker 2019; R Core Team 2019).

Green space-footpath variables of interest that were created for statistical analysis.

Green cover type	Footpath type	Variable name
All green cover	All footpaths	All green-all foot
	Footpaths with traffic	All green-with traffic
	Footpaths with no traffic	All green-no traffic
Woodland	All footpaths	Woods–all foot
	Footpaths with traffic	Woods-with traffic
	Footpaths with no traffic	Woods-no traffic
Tree outside woodland	All footpaths	Trees-all foot
	Footpaths with traffic	Trees-with traffic
	Footpaths with no traffic	Trees-no traffic
Ground cover	All footpaths	Ground-all foot
	Footpaths with traffic	Ground-with traffic
	Footpaths with no traffic	Ground-no traffic

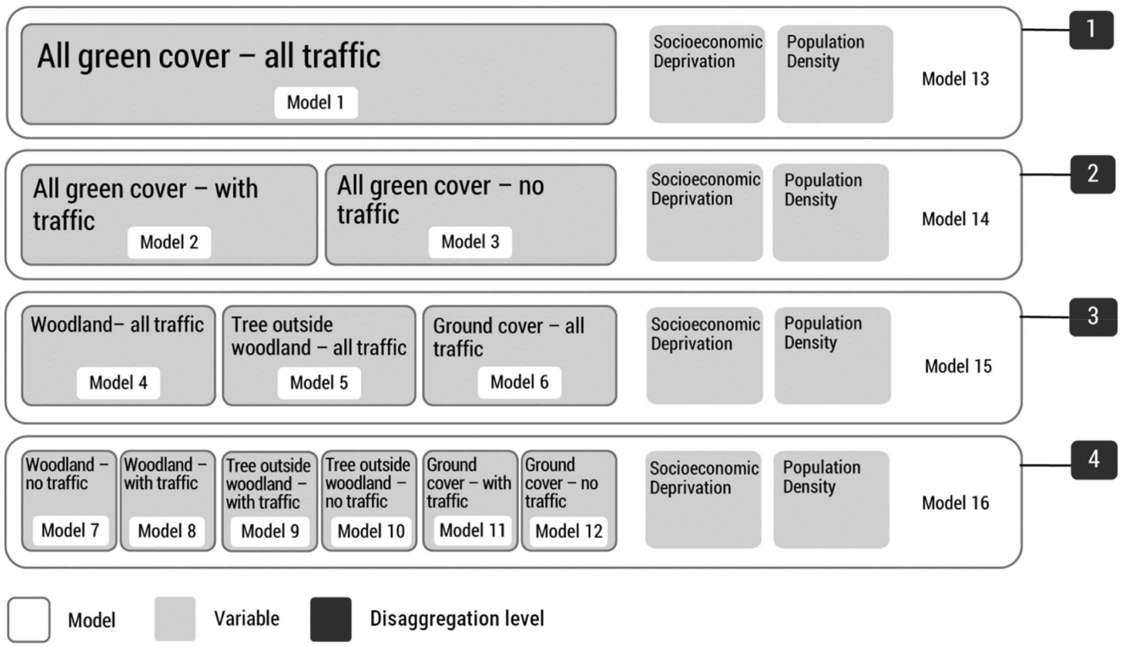
We included socioeconomic deprivation and population density as potential areal-level confounders. Socioeconomic deprivation has been shown to be correlated with green space exposure and is one of main health determinants (Marmot and Bell 2012; Garrett et al. 2019; Belcher et al. 2024). We used the Carstairs index 2011 (Carstairs and Morris 1990), an area-level composite measure of categorised into quintiles as an indicator of socioeconomic deprivation. The Carstairs index was developed for epidemiological applications and is calculable for all COAs in England and Wales using information from the 2011 Census. The index is determined by standardizing and summing four 2011 Census variables at the COA level: male unemployment (economically active males seeking work), overcrowding (households with >1 person per room), car ownership (households with no car), and low social class (head of household in NS-SEC categories 7 or 8).

Population density is inversely correlated with green space (Fuller and Gaston 2009) and correlated with many different aspects of the urban environment that impact on health (Beenackers et al. 2018). Areas of high population density, for example, often have better access to active transport facilities, which encourage physical activity and positively impact health (Stevenson et al. 2016). We derived population density by intersecting the 100 m × 100 m resolution 2011 WorldPop product (Lloyd et al. 2017) with a 1 km buffer from each COA PDWC and extracted the total number of people within said buffer using the (Baston and ISciences 2022) and packages in R.

We produced descriptive statistics and frequency polygons to explore skewness, heteroskedasticity of outcome and exposure variables which can be found in Appendix B (Table B.1. and Figures, B.1. and B.2.).

We used binomial Generalised Linear Models (GLMs) to assess the association between positive self-rated health and our exposure variables, the 12 green space-footpath combinations. To account for over-dispersion due to our dependent variable (the age and sex adjusted ratio of COA residents with positive self-rated health) being a proportion rather than a binary variable, we fitted a quasi-binomial error structure (Dunn and Smyth 2018). To identify any non-linear associations, we applied natural cubic splines with internal knots at the 25th, 50th, and 75th percentile and boundary knots at the minimum and maximum of each exposure variable using the splines package in R (Perperoglou et al. 2019).

Models 1–12 (Figure 2) are only adjusted for age and sex (using direct standardisation), regressing each of our 12 green space-footpath variables against age- and sex-adjusted proportion of people with positive self-rated health. We built four additional models that adjust for potential confounders using covariates (Models 13–16 in Figure 2). All these models include area-level confounders socioeconomic deprivation and population density as covariates as potential confounders. In addition, we adjust for other greenspace-footpath variables within the same level of green space disaggregation, either by green cover type, or by whether there is roadside traffic nearby. This adjusts for potential confounding between green cover types within the same level of green space disaggregation. For example, the area of one green cover type (e.g.) may be positively correlated with another green cover type (e.g.) and



Variables included in models. Each level (1–4) represents a different degree of green space disaggregation. Models 1–12 examine exposures individually, while models 13–16 include all green space exposures from that level alongside area-level confounders (socioeconomic deprivation and population density).

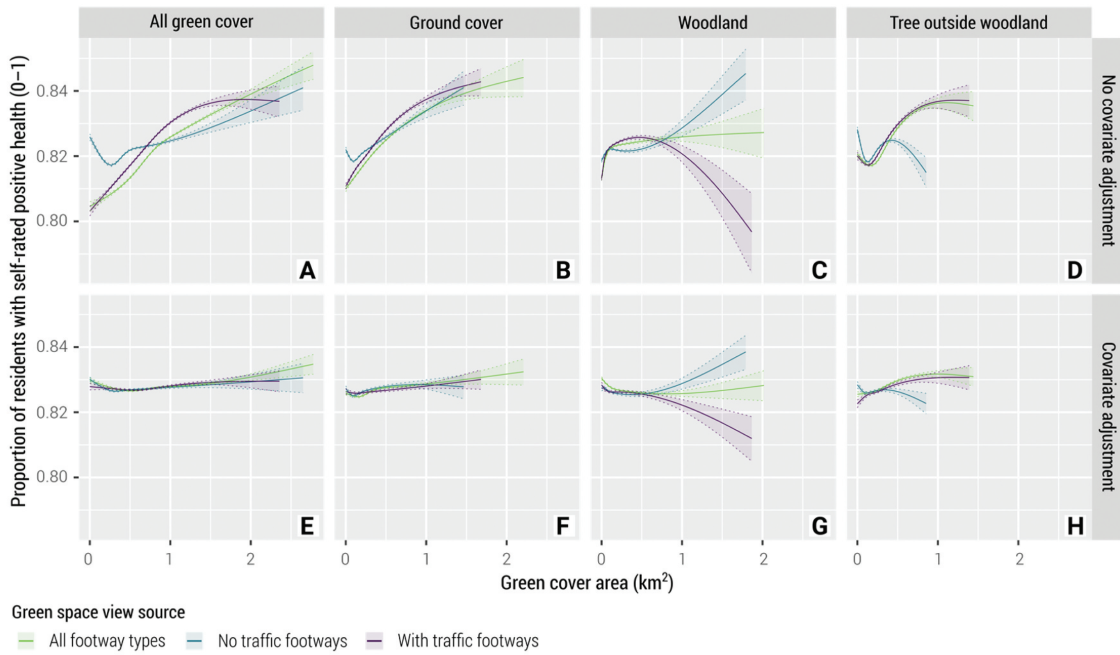
might, therefore, confound any association of with self-rated health. We include disaggregated forms of green cover types (, and) in the same model (Models 15 and 16 in Figure 2). We also include the and measures of the same green cover type in the same model to (Models 14 and 16 in Figure 2).

To assess independence between variables in the same covariate adjusted model (Models 13–16) we calculated covariate Generalised Variance Inflation Factors (GVIF) (Fox and Monette 1992) using the package (Murphy 2020). We transformed our GVIFs to the more commonly used variance inflation factor scale, to assess collinearity. A covariate GVIF between 1 and 2.5 was taken as acceptably colinear, following guidance for epidemiological ecological studies (Johnston et al. 2018), which was the case for all models (see Appendix B Table B.2. for GVIF scores).

Results

Across the 146,970 urban COAs, the mean age- and sex-standardised proportion of residents reporting positive health was 0.80 (SD: 0.07, IQR: 0.75–0.85), following a slightly negatively skewed distribution. Conversely, the area of experienceable green cover was positively skewed across all exposures, with fewer recorded exposures at larger quantities. On average, COAs had 0.82 km^2 (SD: 0.36) of total green cover visible from all available footpaths. When disaggregated by vegetation type, ground cover was the most prevalent visible green space (mean: 0.38 km^2, SD: 0.26), followed by trees outside woodland (mean: 0.28 km^2, SD: 0.16) and woodland (mean: 0.16 km^2, SD: 0.18). Full summary statistics, including variables stratified by traffic presence, are detailed in Appendix B (Table B.1).

Increasing all types of green space visible from any foot path type had positive associations with self-rated health before adjustment (Figure 3). Covariate confounder adjustment in models 13–16 attenuated the effect sizes for all green space variables (Figure 3(e-h)). After adjustment and had mostly positive J-shaped associations with self-rated health (Figure 3(e,f)) and had a mostly positive S-shaped association. Associations were inconsistent for which had a U-shaped association (Figure 3(g)). A version of Figure 3 with a -axis scaled for each variable is available as Figure C.1. in Appendix C Figure A3.



Predicted effects of green cover visible from footpaths on the directly age-sex standardised proportion of census output area resident with self-rated positive health from binomial generalised linear models. Dotted lines with shaded areas show 95% confidence intervals. The top row shows predicted effects of each green cover–traffic combination from models 1–12 (no covariate adjustment). The bottom row shows predicted effects after covariate adjustment (models 13–16). All predictions and confidence intervals were back-transformed from logit scale to proportions. Continuous covariates were held constant at their mean levels and deprivation and population density were held constant at their third quintile in covariate adjusted models. Figure C.1. In Appendix C shows the same data with independent *y*-axis scales for each panel to see within variable differences more clearly.

We saw little evidence that associations differed by traffic adjacent to footpaths for and (Figure 3(e,f)). For and associations diverged markedly with the absence and presence of traffic, albeit in opposite directions (negative and positive respectively, Figure 3 (g,h)). The negative divergence associated with traffic was more pronounced if the visible area of was larger than 1 km^2 with no difference in associations for values below 0.5 km^2. At the highest level of COA exposure to (1.72 km^2), 83.7% (95% CI 82.63–84.72) of the population rated their health as positive if experienced from footpaths without traffic, compared to 78.59% (95% CI 77.3–79.82) if experienced from footpaths with adjacent traffic (holding deprivation and population density at their third quintile) a difference of 5.11%. Differences in associations based on traffic were consistent across the range of , but less pronounced than (Figure 3(h)).

Increasing all green-traffic variables aside from - and from 0 km^2 by a relatively small amount (~0.2 km^2), had a sharp negative association with self-rated health in adjusted models (Figure 3(e-h) and Figure C.1.).

In terms of confounder – health associations, the four covariate adjusted models (Models 13–16) the self-rated positive health of people in the least deprived areas was 15.87–16.01% higher than those living in the most deprived areas (Figure D.1., Appendix D). The proportion of residents with self-rated positive health in the highest population density areas was 2.00–2.20% higher than those in the lowest population density areas (Figure D.2. Appendix D).

Discussion

Our study aimed to investigate the relationship between experiencing green space near to home and health, and whether this relationship is modifiable by simultaneous experience of traffic, an external factor to green space. Across all urban COAs in England and Wales we found mostly positive self-rated health associations with three of the four types of green space cover types we investigated (all green cover, ground cover and tree outside woodland). This positive effect is consistent with what most studies investigating associations between green space and a variety of health indicators have found, according to a recent systematic review (Yang et al. 2021). Associations with were not modified by traffic (Figure 3(e)); however, traffic did modify associations for some green space subtypes. The divergence in associations was most prominent for visible from available footpaths, with negative associations observed for footpaths with adjacent traffic and positive associations for footpaths without traffic, after covariate adjustment (Figure 3(g)). Positive self-rated health associations with were in the opposite direction, with positive associations for footpaths with adjacent traffic and negative association for footpaths with no traffic (Figure 3(h)). No difference in associations with was detected (Figure 3(f)).

The positive association of visible from footpaths without adjacent traffic with self-rated health may be due no traffic environments seeming more tranquil (Chu et al. 2025), the most natural and being able to support more biodiversity. There is evidence that perceived biodiversity positively impacts mental health associations (Marselle et al. 2019; Methorst 2024). Biodiversity in woodland away from roads is generally higher (Polak et al. 2013). A lack of traffic may also make seem more natural (Knez et al. 2018) and add a sense of "being away" from urban experiences, which is a mechanism of cognitive restoration in Attention Restoration Theory (Kaplan 1995). Reduced stress and enhanced cognition may lead to COA residents to self-rate their health as positive (Levinson and Kaplan 2014; Liu et al. 2018). The negative association of visible from footpaths with adjacent traffic may be plausibly explained by these footpaths being less appealing for walking (Tainio et al. 2021), resulting in residents undertaking less physical activity, worsening their health and perceived health (which is correlated with health).

The positive associations observed for visible from all footpaths and footpath with adjacent traffic support previous findings that sparse trees alongside roads with traffic, for example, street trees, are associated with better self-rated health (Reid et al. 2017).

We found associations of similar magnitude and shape for associations of ground cover visible from footpaths with and without adjacent traffic. Parks in urban spaces are often classified as (a type of ground cover) in the LCM2017 (Morton et al. 2011). A higher availability of parks has been linked to increases in physical activity (Kaczynski and Henderson 2007). visible from footpaths with adjacent traffic, for example, road verges, may positively impact health through similar mechanisms such as improving aesthetics, increasing exertion, reducing stress and cognitive fatigue (O'Sullivan et al. 2017). There has been little empirical research or theory development; however, on the benefits of adjacent to roads (Säumel et al. 2016; O'Sullivan et al. 2017). However, recent work has found that amongst many other benefits, more biodiverse, free-growing roadside verges are more attractive to residents (Southon et al. 2017), which is a mediator towards increased physical activity.

We found little evidence that associations differed by traffic for visible from footpaths (Figure 3(e)). This is likely due to the opposite association for without traffic and with traffic adjacent to footpaths, which was of similar magnitude and, therefore, potentially counteracting when aggregated to . This highlights the importance of disaggregating green space green cover into separate types as causal pathways and the influence of traffic might differ by said types.

Our findings also highlight the substantial role of increasing socioeconomic deprivation on poorer self-rated health (an approximate 16% point difference). This was considerably larger in magnitude than the associations observed for green space. Population density had a much smaller magnitude of association (~2%), which was more comparable to the scale of the green space exposures.

Our exposure assessment only included green space that was from footpaths near to where people live. This moves beyond studies which use buffers from footpaths which don't remove views blocked by buildings (Carthy et al. 2020), or most studies that do not integrate the visibility of green space from points where it can be viewed at all (Labib et al. 2020). Most equate residential green space exposure as the distance to nearest green space, green space in their local area or within a 0.4 km^2–2 km^2 radius around their home (Labib et al. 2020). To identify visible areas along a footpath we implemented an isovist model in R (see Appendix A). We invite future researchers to use this model (which can be accessed here: https://rpubs.com/richardneilbelcher/

isovist), particularly when assessing the visibility of areas from footpaths in urban environments for large-scale exposure assessments, where a three-dimensional viewshed analysis is too computationally intensive. This was the case for us as we had > 7 million viewpoints.

Our study covered the diversity of people found across urban areas in England and Wales according to the 2011 census. This gives our analysis a high level of external validity allowing strong generalisability to the population of England and Wales into the future. Our large totally inclusive population also increases the generalisability of our results to populations in other countries with similar demographics. However, as a cross-sectional study, we have the inherent limitation of only investigating associations between green space and health. It may be that there are additional confounders we did not account for driving these associations.

Our analysis took a simplified view of roadside traffic, as we were not able to differentiate between low trafficked and high trafficked roads next to footpaths. Effect modification may have varied by a more specific amount of traffic and should be investigated in further research.

Likert or semantic differential scale metrics of self-rated health such as we have used also have well-known biases. As the outcome is self-assessed individuals may rate their health lower or higher to try and enact policy change for example (strategic voting bias) (Vossler and Evans 2009). Differences in what respondents perceive to be positive health may lead to individuals with the same objectively measured health status (physical and mental) rating their health differently. This variance in scale use could generalise to sub-populations. For example, one sub-population could systematically undervalue their health or not understand their health, this may cause some confounding with green space and health associations (Mühlbacher et al. 2016). For example, deprived populations systematically overestimating their good health and being in an area with less green space, which would cause the magnitude of the true green space-health association to be underestimated.

A limitation of our study is the temporal mismatch between the health outcome data (2011 Census) and the environmental exposure data (2015–2018). While urban green infrastructure is generally stable over short periods, we recognize that changes in local green cover or population demographics during this interval may not be fully captured.

Our finding that some green space green cover types were modified by traffic supports investigation of potential factors that influence green space – health associations more generally, which are relatively understudied (Marselle et al. 2021). Furthermore, the fact we only found diverging associations for some green cover types, highlights that it may also be important to disaggregate green space by green cover type when investigating other influencing factors in future analyses where possible.

As one of the first studies to investigate how simultaneous exposure to traffic may impact green cover and health associations, our findings should be replicated. This could be similar analysis using different outcomes or study areas. Longitudinal analyses or experiments on traffics modifying effect on green space health associations would allow for an exploration of whether our associations are causal. For example, comparing the change in health of individuals which are randomly assigned to either experiences of green space near a road or away from a road.

Architects, urban planners, and policymakers should consider the important role that traffic may play in impacting the benefits green space can have to human health. Our results support the presence of trees outside woodland in urban areas by roads and conversely, woodland away from roads for human health benefits to those living nearby.

Conclusion

Our study provided an exploratory systematic comparison of the effect that traffic adjacent to footpaths had on natural environments association with self-rated health of all 45.7 million urban residents of England and Wales in our study. We linked the self-rated health responses of these individuals from the 2011 census with measures of natural environment experiences adjacent to and away from roads with traffic. Neighbourhood green space ( ) had mostly positive associations with health, when experience-able from any footpath. Traffic had little impact on self-rated health and neighbourhood and neighbourhood all associations. However, the proportion of residents self-rating their health as positive in a neighbourhood increased when there was more with no traffic nearby and decreased when they had more . Conversely, had the strongest positive association with self-rated health when experienceable from footpaths adjacent to roads with traffic. Our findings highlight the importance of considering how exposures concurrent to natural environments can modify whether and to what degree green spaces benefit health.

Abbreviations

COA	Census Output Area
Copernicus TCD	Copernicus Land Monitoring service Tree Cover Density product
GLM	Generalised Linear Model
GVIF	Generalised Variance Inflation Factors
LCM2017	Land Cover Map 2017
ONS	Office for National Statistics
OS	Ordnance Survey
PDWC	Population Density Weighted Centroid
WHO	World Health Organisation

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Author contributions

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