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Benefit of woodland and other natural environments for adolescents' cognition and mental health

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Epidemiological studies have established positive associations of urban nature with cognitive development and mental health. However, why specifically these health benefits are received remains unclear, especially in adolescents. We used longitudinal data in a cohort of 3,568 adolescents aged 9 to 15 years at 31 schools across London, UK, to examine the associations between natural-environment types and adolescents' cognitive development, mental health and overall well-being. We characterized natural-environment types in three tiers, where natural space was distinguished into green and blue space, and green space was further distinguished into woodland and grassland. We showed that, after adjusting for other confounding variables, higher daily exposure to woodland, but not grassland, was associated with higher scores for cognitive development and a lower risk of emotional and behavioural problems for adolescents. A similar but smaller effect was seen for green space, but not blue space, with higher scores for cognitive development. Our results suggest that urban planning decisions to optimize ecosystem benefits linked to cognitive development and mental health should carefully consider the type of natural environment included.

The past decades have seen a tremendous population growth in urban areas, which is linked to a number of various human health effects[1,2], including risks of developing cognitive problems and mental-health issues[3,4]. Understanding the dynamic interactions attributed to higher risks of cognitive problems and mental-health issues in urban areas, which until now remain unclear, is important. Emerging evidence suggests that exposure to natural environments plays an important role for cognitive development and mental health[5–7]. The benefit of natural environments to mental health has been suggested to be comparable in magnitude to family history and parental age, higher than the degree of urbanization and lower than parents' socioeconomic status[6]. Sensory and non-sensory pathways have been suggested as potentially important for delivering cognition and mental-health benefits received from nature exposure[8–13]. Further research into these pathways is fundamental to establishing a mechanistic pathway between nature and mental health.

One of the barriers to understanding associations among natural environments, cognitive development and mental health is the use of inconsistent exposure definitions. Nature exposure has been measured, among others, as physical access to nature[14], natural-environment type[15,16], nature dose[17] and degree of urbanization[6,17]. Wider-scale epidemiological research studying the association between nature and mental health has almost exclusively measured 'greenness' through vegetation indices such as the Normalized Difference Vegetation Index (NDVI), a unitless index of relative overall vegetation density and quality[5–7,18]. NDVI tends to simplify greenness without differentiating between the types of natural environment that exist, such as grassland or woodland. However, woodland has been proposed to generate a more restorative effect both psychologically[16,19] and physiologically[12], showing that woodland has a more restorative effect when compared with overall urban green space, agricultural land or wetland, among others[16,19]. In addition, NDVI does not account for standing and flowing water bodies such as lakes, rivers or reservoirs (blue space), yet these have been associated with mental health and cognitive development[18,20].To date, there is no comprehensive analysis or agreement on which measure of environmental exposure is more or less important.

Many studies have focused on adult assessments of exposures to natural environments in relation to mental health[21]. However, there is growing recognition of the importance of focusing on children and adolescents, who are in the midst of their cognitive and mental development[22]. For example, 1 in 10 of London's children and adolescents (~111,600 persons) between the ages of 5 and 16 suffers from a clinical mental-health illness, and excess costs are estimated to be between £11,030 and £59,130 annually for each person. As for adults, there is evidence that natural environments play an important role in children and adolescents' cognitive development and mental health into adulthood[6,7,23]. However, many of these studies tend to exclude or simplify the distinct types of natural environment, despite the fact that particular types, such as blue space or woodlands, have been suggested to influence children and adolescents' mental health[18,24]. To date it remains unclear how different types of natural environment influence adolescents' cognitive development and mental health.

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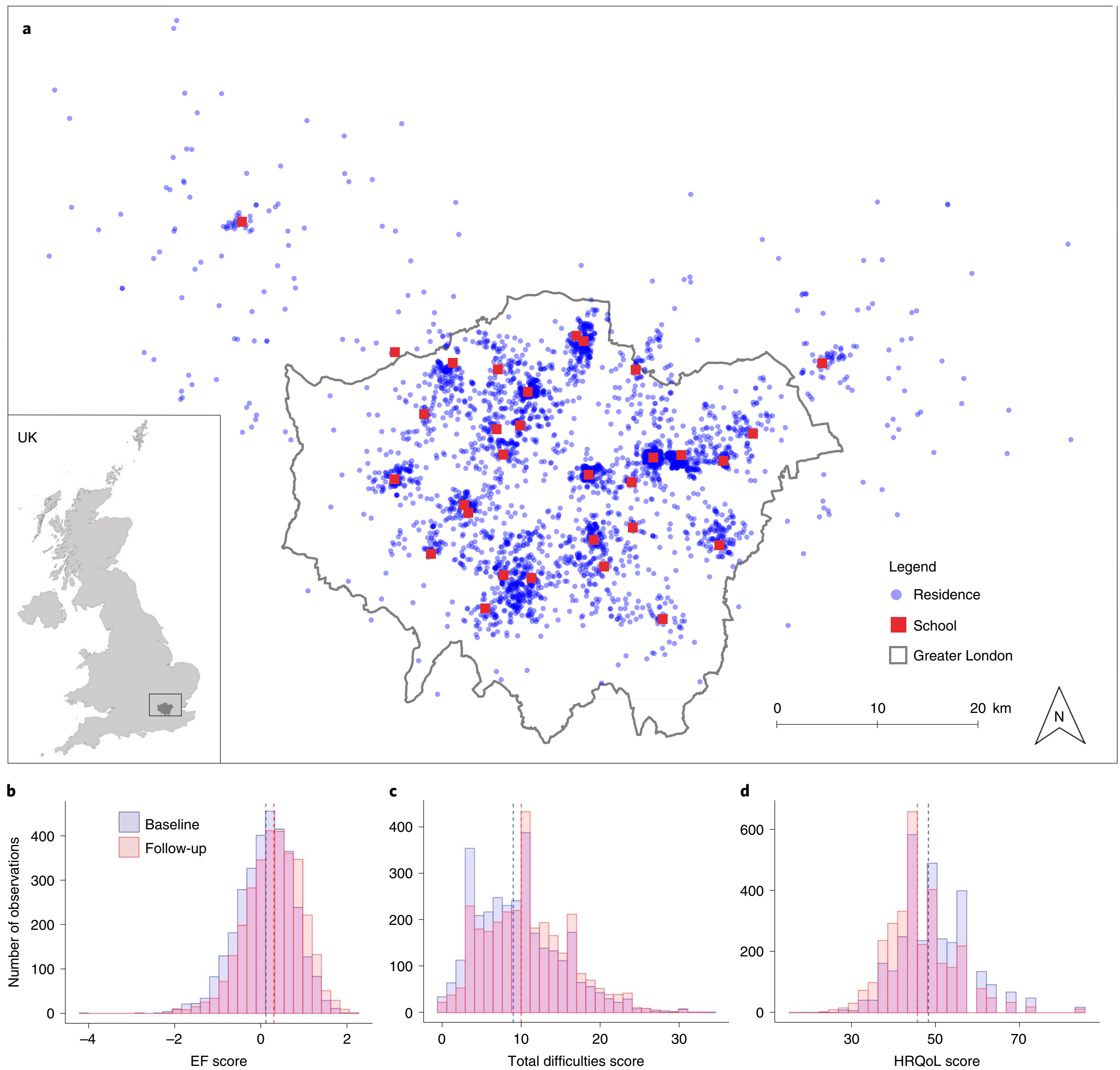

Fig. 1 | Geographic distribution of our study population and associated health variables for cognitive development, mental health and overall well-being. **a**, Residential locations during the second (t_1) visit of the 3,568 adolescents with a known residence during the first (t_0) and second visit of SCAMP and the 31 participating schools across the London metropolitan area, UK. **b–d**, Histograms show our t_0 (blue) and t_1 (red) outcomes for cognitive development: EF score and our outcomes for mental health and overall well-being (**b**); SDQ total difficulties score (**c**); and KIDSCREEN-10 Questionnaire HRQoL score (**d**). A dashed line marks the median (first quartile–third quartile) for our t_0 and t_1 outcomes: t_0: 0.16 (−0.30, 0.56), t_1: 0.33 (−0.10, 0.76) (**b**); t_0: 9 (6, 13), t_1: 10 (7, 14) (**c**); t_0: 48.28 (43.34, 53.10), t_1: 45.66 (41.23, 49.76) (**d**).

In this study, we estimated the contribution of natural-environment types to adolescents' cognitive development and mental health to inform future urban planning decisions. We analysed a longitudinal dataset of 3,568 adolescents between 2014 and 2018 with a known residence from the Study of Cognition, Adolescents and Mobile Phones (SCAMP)[25] across the London metropolitan area in the UK (Fig. 1a).

We assessed cognitive development, mental health and overall well-being. We measured cognitive development through a composite executive function (EF) score using computerized tests (Fig. 1b), mental health through self-reported questionnaires on emotional and behavioural problems using the Strengths and Difficulties Questionnaire (SDQ) total difficulties score (Fig. 1c), and overall well-being using the KIDSCREEN-10 Questionnaire Health-Related Quality of Life (HRQoL) score (Fig. 1d). A higher EF score indicated better cognitive performance, while higher SDQ total difficulties and HRQoL scores indicated worse mental health and overall well-being, respectively. We systematically mapped urban natural environments to identify each adolescent's daily exposure rate (DER) around their residence and school within 50 m, 100 m, 250 m and 500 m in a three-tier stepwise characterization of natural environments: (Model I (M I)) natural space, (Model II (M II)) green versus blue space and (Model III (M III)) grassland versus woodland. Grassland and woodland were characterized as green space lower and higher than 1 m, respectively.

Our models identified an important protective factor of woodland exposure for adolescents' cognitive development and mental health. Unless stated otherwise, our results were based on fully adjusted models with natural-environment DERs with a daytime weighting and measured in buffer areas of 250 m (Methods).

Results

The impact of natural-environment type on outcomes. We estimated the change in adolescents' cognitive development, mental health and overall well-being for each type of natural environment by fitting multilevel longitudinal regression models using Bayesian statistics (Supplementary Methods 1). We found that adolescents' cognitive development improved with higher DER to natural space. When comparing those adolescents exposed to the highest level of natural space (~92%) with those exposed to the lowest level of natural space (~1%), we estimated a percentage change in cognitive development of 2.14% (95% credible interval (CI): 0.42, 4.29) using the EF score (Fig. 2a and Supplementary Fig. 1a). We also provided the results for the SDQ total difficulties score and HRQoL score with natural-space DER (Fig. 2b,c and Supplementary Fig. 1b,c), where we found no improvement of mental health and overall well-being with higher DER to natural space, meaning the 95% CI included the null effect for both models. Our M II results for green-space DER were almost identical to the M I results for natural-space DER. This is probably due to a high correlation between our DERs for natural space and green space since adolescents' DER to blue space was generally low (Supplementary Table 1). This also meant that our models did not find an improvement of adolescents' cognitive development, mental health and overall well-being with DER of blue space (Fig. 2 and Supplementary Fig. 2).

To further assess the role of different types of natural environment in adolescents' cognitive development, mental health and overall well-being, we characterized green space into two distinct natural-environment types: grassland and woodland. We found that a higher DER to woodland was associated with higher scores for cognitive development and a lower risk of emotional and behavioural problems for adolescents. When all other confounding factors were held constant, there was a beneficial contribution to cognitive development by 0.42 (95% CI: 0.21, 0.57) points using the EF score and a reduction in the risk of emotional and behavioural problems by −0.17 (95% CI: −0.32, −0.03) points using the SDQ total difficulties score (Fig. 2 and Supplementary Fig. 3). We found no improvement of overall well-being with higher DER to woodland (Fig. 2c and Supplementary Fig. 3c). When comparing those adolescents exposed to the highest level of woodland (~38%) to those exposed to the lowest level of woodland (0%) in our study, we estimated a percentage change in cognitive development of 6.83% (95% CI: 3.41, 9.11) using the EF score and a percentage change in the risk of emotional and behavioural problems of −16.36% (95% CI: −27.49, −3.50) using the SDQ total difficulties score. We found no improvement of adolescents' cognitive development and mental health with a higher DER to grassland with the exception of our outcome for overall well-being using the HRQoL score (Fig. 2 and Supplementary Fig. 3).

The role of other factors. We fitted our longitudinal models with a number of other factors to account for demographic, environmental and socioeconomic factors that are known to influence adolescents' cognitive development and mental health[26,27]. We found that our outcomes for adolescents' cognitive development, mental health and overall well-being were influenced by a variety of other factors such as the adolescent's age, ethnic background, gender, parental occupation and type of school (Supplementary Tables 2, 3 and 4). When compared with independent schools for example, state schools were predicted to result in a negative contribution to adolescents' cognitive development, mental health and overall well-being by a percentage change of −5.10% (95% CI: −6.05, −4.30) using the EF score, a 10% (95% CI: 5, 15) increase in the risk of emotional and behavioural problems using the SDQ total difficulties score and an increase in odds of exhibiting low overall well-being by 57% using the HRQoL score (95% CI: 19, 104). We also found that air pollution appears to be unstable in our models, influencing adolescents' cognitive development in some but not all models using the EF score (Supplementary Table 2). When removing demographic, environmental and socioeconomic factors from our models, we showed that modelled environmental variables were, in general, tenfold smaller than the contribution of our demographic and socioeconomic variables (Supplementary Table 5). This stepwise exclusion of fixed effects from our models highlights the relative importance of our demographic and socioeconomic variables to adolescents' cognitive development and mental health.

To test the robustness of our findings, we did a series of sensitivity analyses to assess which models perform best for evaluating the association between natural-environment types and adolescents' cognitive development, mental health and overall well-being. This included testing each adolescent's DER for (1) different buffer areas around their residence and school and (2) a different weighting based on a full-day (24 hours) instead of a daytime (12 hours) weighting (Methods). For our analyses of different buffer areas, we found that our results were consistent across different buffer areas, but some models did suggest a weaker association with smaller buffer areas when compared with larger buffer areas (Supplementary Figs. 1, 2 and 3). When using a different weighting for our DER, we found that our models showed consistent patterns when we modelled with a DER based on a daytime or full-day weighting (Supplementary Tables 2, 3 and 4).

Discussion

To our knowledge, this is the largest epidemiological study to report on the impact of natural-environment-type exposure on cognitive development, mental health and overall well-being during adolescence. Our models demonstrated that higher exposure to woodland was associated with a beneficial contribution to cognitive development and a lower risk of emotional and behavioural problems during adolescence. We also found that exposure to green space was associated with a beneficial contribution to cognitive development, while there was a weaker association for our mental-health and overall well-being outcomes. Finally, we did not find a consistent association of blue space or grassland exposure with all outcomes. These findings contribute to our understanding of natural-environment types as an important protective factor for adolescents' cognitive development and mental health and suggest that not every natural-environment type may contribute equally to these health benefits.

Overall, we observed that woodland exposure was associated with a beneficial contribution to cognitive development and a lower risk of emotional and behavioural difficulties during adolescence. This is in line with previous reports of woodland's positive impacts on physical and mental health[12,16,28], with the exception of a study performed in central Scotland[29]. Forest bathing, for example, is a relaxation therapy that has been associated with physiological benefits, supporting the human immune function, reducing heart rate variability and salivary cortisol, and various psychological benefits[12,28]. However, the hypothetical mechanisms for why we experience these psychological benefits from woodland remain unknown. One possible explanation may be that audio–visual exposure through vegetation and animal abundance provides psychological benefits, of

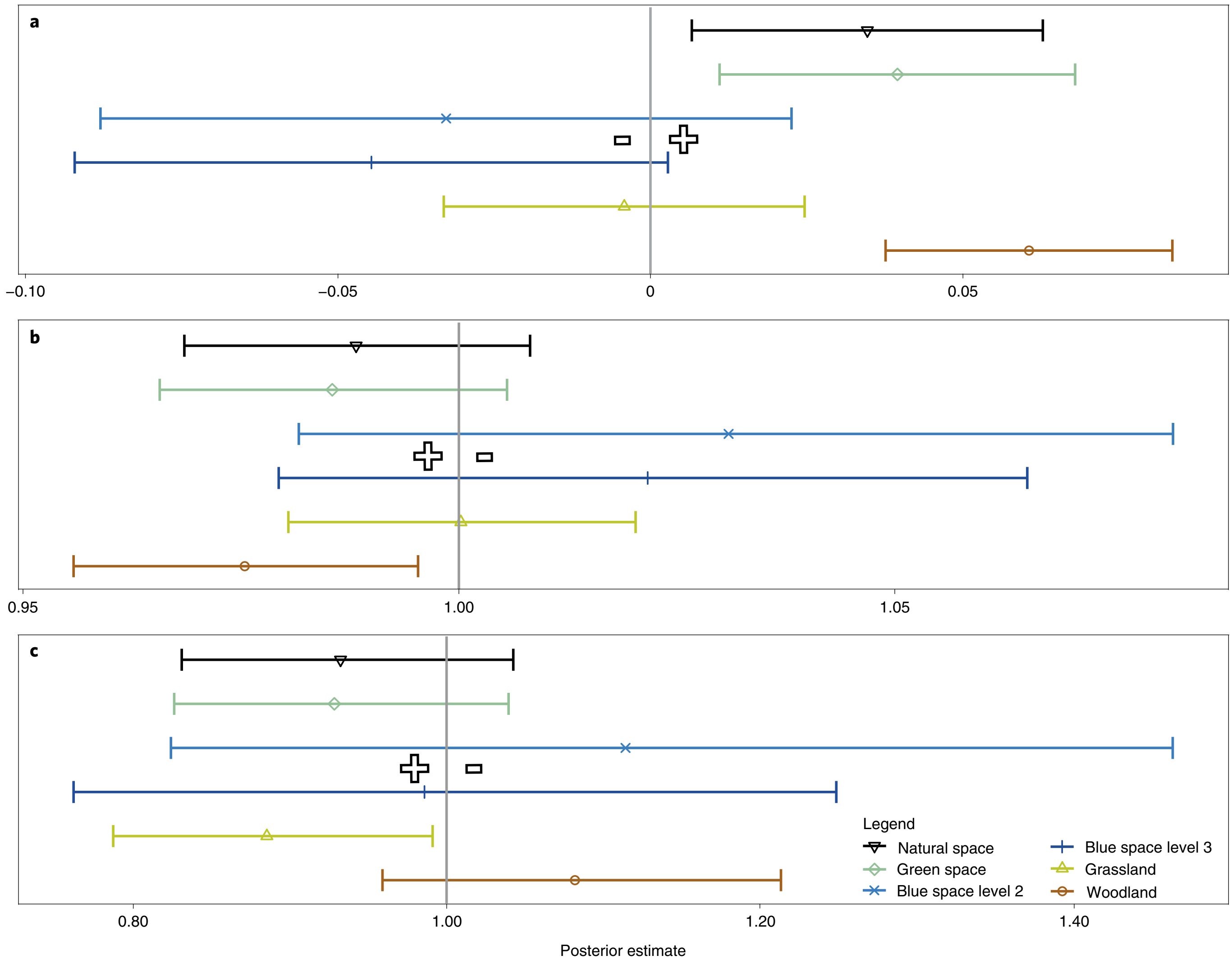

Fig. 2 | Effects and 95% CIs of natural-environment type DER with cognitive development, mental health and overall well-being across London. **a**–**c**, The association of EF score (**a**), SDQ total difficulties score (**b**) and KIDSCREEN-10 Questionnaire HRQoL score (**c**) with the natural-environment-type DER of Model I: natural space (black); Model II: green space (light green), blue space level 2 (light blue) and blue space level 3 (dark blue); and Model III: grassland (yellow) and woodland (brown). Fully adjusted model was plotted with posterior mean and 95% CI. The vertical line (grey) is the reference line and is set to zero or one depending on the model used for the outcome in analysis. Hollow plus or minus signs indicate whether the association had a positive or negative contribution towards high cognitive development/good mental health (versus low cognitive development/poor mental health).

which both features are expected in higher abundance in woodland[10,30]. Although our results show that urban woodland is associated with adolescents' cognitive development and mental health, the mechanistic pathway to explain this association remains unknown.

Our results also showed that exposure to green space, but not blue space, was associated with a beneficial contribution to adolescents' cognitive development, consistent with previous studies[7,31]. We found weaker associations of mental-health and overall well-being outcomes with exposure to green space, and this is consistent with the variability in these relationships found in previous studies[5,6,14,32]. It may be that most studies, including this one, do not account for quality indicators of green space such as accessibility or usability, which has been proposed to have a beneficial contribution to mental health[33].

We did not find a consistent association between blue-space exposure and outcomes, despite other studies having found associations[18,34]. This association cannot be discarded on the basis of our study because 66.8% of participants had no blue space within 250 m, and so the amount of blue space surrounding adolescents' residences and schools was low regardless. One explanation for this weak association may be the changing natural-environment types from one city to another, potentially changing a person's attachment to nature[35]. Residents in coastal cities, for example, may have a different relationship with blue space compared with residents of cities inland where blue space may be less abundant[36]. People's relationship with their local nature may be key to understanding the cognition and mental-health benefits received from nature exposure. Alternatively, inconsistencies may be the result of different sampling techniques. For example, other studies have used self-reported blue-space visitation rates or blue-space visibility and found associations with behavioural difficulties and psychological distress[18,34]. Inconsistencies due to different sampling techniques make it difficult to harmonize results into a consistent framework, but to date there has been no comprehensive analysis allowing for harmonization of nature-exposure data.

Our findings suggest a stronger association with a 250 m and 500 m buffer area (which included surrounding natural environments further away from the adolescent's residence and school)

Table 1 | Cohort characteristics of the 3,568 adolescents with a known residence during the first (t_0) and second (t_1) school visit

	n = 3,568	
	Median	**IQR**
Age (years)	12.96	12.02–14.22
Parental occupation	***n***	**%**
Managerial/professional occupations	2,077	58.21
Intermediate occupations	292	8.18
Small employers/own-account workers	507	14.20
Lower supervisory/technical occupations	161	4.51
Semi-routine/routine occupations	398	11.15
Missing/not interpretable	133	3.72
Area-level deprivation		
Least deprived (Qn1)	580	16.25
Qn2	561	15.72
Qn3	620	17.37
Qn4	747	20.93
Most deprived (Qn5)	1,058	29.65
Missing	2	0.05
Gender		
Female	2,069	57.98
Male	1,499	42.01
Ethnicity		
White	1,617	45.31
Black	523	14.65
Asian	959	26.87
Mixed	406	11.37
Other/not interpretable	31	0.86
Missing	32	0.89
Type of school		
State	2,556	71.63
Independent	1,012	28.36

Data from t_0 and t_1 were based on participants who took part in the computer-based assessment. Parental occupation is based on the highest National Statistics Socio-economic Classification level (five-group version) of either parent. Qn1, Qn2, Qn3, Qn4 and Qn5 of area-level deprivation represent the first, second, third, fourth and fifth quintiles of the Carstairs deprivation index, respectively. Full cohort characteristics during t_0 and t_1 are available in Supplementary Table 6. IQR, interquartile range.

when compared with a 50 m and 100 m buffer area (which included surrounding natural environments immediately adjacent to the adolescent's residence and school). This suggests that natural environments further away from the adolescent's residence and school may play an important role for adolescents' cognitive development and mental health. This contrasts with the hypothesis that immediate surroundings may be more relevant for mechanisms of psychological restoration[18] and raises questions on the role of natural environments further away from a residence or school for receiving cognitive-development and mental-health benefits. At present, conceptual frameworks on nature and mental health discuss proximity to nature as a key component for assessing a person's exposure to nature, but until now it remains unclear at what distance, if any, natural environments become less relevant to a person's cognition or mental health[37,38]. Further research to resolve this critical knowledge gap can be fundamental to understanding the pathway from nature exposure to health benefits.

The study has several strengths. It used a high-quality, large epidemiological cohort dataset reporting on the impact of natural-environment types on the cognitive development, mental health and overall well-being of adolescents, an understudied subset of the urban population. This large sample had substantial spatio-temporal diversity on an urban scale for the London metropolitan area with sufficient statistical power to investigate interactions. The study used clinically validated instruments to define adolescents' cognitive development, mental health and overall well-being. Previous studies have used satellite remote-sensing data for establishing associations of green space with cognitive development and mental health. In this study, we developed a quantitative measure of exposure by combining satellite, light detection and ranging (LiDAR) and other data as a proxy for characterizing natural-environment types. This includes geographical data of high resolution to develop measures of natural-environment DER such as NDVI at 10 m resolution and LiDAR data at 2 m resolution. This study also adjusted for other potential confounders through objective measures of air pollution exposure, socioeconomic status and other individual-level factors. For example, lower access to woodland may also be an added risk factor among more vulnerable groups in society. Likewise, ensuring fair and equitable access to woodland can be an important tool to manage and minimize cognitive-development and mental-health problems, especially in adolescents who are transitioning into adulthood.

A number of potentially confounding factors could have influenced our results. For example, the assumption that adolescents' DER to natural environments leads to increased use of natural environments may not always hold because indicators such as accessibility or usability of natural environments may also play a role[18,33]. Our data also did not provide information on when exactly adolescents moved to a new residence between the first and second visit, which may influence our DER measure. In addition, the contribution of environmental factors was, in general, tenfold smaller than that of our demographic or socioeconomic variables, suggesting that increasing nature exposure may not suffice to improve adolescents' cognitive development and mental health. In addition, a considerable proportion of our participants (58.21%) were considered part of the group whose parents had a managerial/professional occupation, indicating adolescents in less-favourable socioeconomic groups may be underrepresented in this study (Supplementary Table 6). While our results are generalizable to most schools in the country, pupils requiring special needs may be differently affected compared with the general school-age population of the UK. Added to this, unmeasured variables such as crime rates may also influence our results[39]. Finally, further research is needed to understand the mechanistic pathway for the higher benefits received from woodland over other natural-environment types.

Methods

Study population. We use data from SCAMP[25], a longitudinal cohort study established to investigate how the cognitive development and behaviour of adolescents across the London metropolitan area might be affected by use of mobile phones and other technologies that use radio waves. A first (baseline or t_0) and second (follow-up or t_1) school visit were carried out between 2014 and 2018 with a time gap of approximately two years between the first and second visits for each school. Initially, 6,612 adolescents participated to the first visit, and 5,208 adolescents participated to the second visit. Our cohort is an open cohort where adolescents could enter after the first visit, and a total of 3,791 adolescents participated to both the first and second visit. For our analysis, we used a subset of 3,568 adolescents who had a known residence during the first and second visit (Fig. 1a and Table 1). Of these 3,568 adolescents, 607 (~17%) moved residence between the first and second visit. This subset excluded eight schools due to low sampling size (<15 adolescents per school). Included adolescents were on average 12 and 14.2 years old during the first and second visit, respectively, and 57.9% of them were female (Table 1). The adolescents (n = 3,568) were part of 31 schools across London, of which 12 were independent schools and 19 were state schools. Of the 31 participating schools, 3 were located outside the Greater London Authority (GLA) administrative area (Fig. 1a). During the assessments, information was gathered on age, gender (two levels: female or male), ethnicity (five levels: White, Black, Asian, mixed or other), school type (two levels: state or independent), parental occupation (five levels: managerial/professional occupations, intermediate occupations, small employers/own-account workers, lower supervisory/technical occupations or semi-routine/routine occupations)[40], and area-level deprivation (divided into quintiles ranging from category 1 'least deprived' to category

5 'most deprived'). We used the Carstairs deprivation index, an area-level composite measure of deprivation to identify socioeconomic confounding[41]. The Carstairs index consists of four variables from the UK Office of National Statistics 2011 Census: proportion of low social class, lack of car ownership, household overcrowding and male unemployment[42]. We categorized the Carstairs deprivation score into quintiles to explore the relative deprivation across areas within which adolescents live. Further characteristics of the study population are presented in Table 1 and Supplementary Table 6. All parents or guardians signed the informed consent and the study was approved by the Health Research Authority North West Haydock Research Ethics Committee (reference: 14/NW/0347).

Outcomes. Adolescents' cognitive development was assessed through a composite score of three computerized EF tasks (backwards digit span, spatial working memory and trail-making task)[43–45]. Versions of these tasks are widely used in EF literature. EF composite was calculated only for adolescents who completed all three contributing tasks. We derived the EF composite at t_0 by taking an average of Z-scores for the key performance measure for each EF task[46]. The composite score at t_1 was derived by taking an average of scores for the same EF tasks, equivalently adjusted by the mean and s.d. from the t_0 performance. The Z-scores and adjusted values were calculated across the whole population at each timepoint. Trail-making task and spatial working memory values were reverse coded before taking the average. EF values are continuous, and higher EF values indicate better cognitive performance (Fig. 1b).

We assessed adolescents' mental health and overall well-being from the self-reported SDQ and the KIDSCREEN-10 Questionnaire taken by each adolescent[47]. The SDQ total difficulties score assesses the emotion and behaviour of adolescents and was calculated by summing the scores for the four difficulties subscales on emotional problems, conduct, hyperactivity and peer problems. Each subscale comprises five items that can be scored 0, 1 or 2, and each subscale score can therefore range from 0 to 10. An SDQ total difficulties score was treated as count data where a higher value represented more behavioural difficulties (Fig. 1c)[47]. The Cronbach's α for the SDQ in our first and second visit samples was 0.79 and 0.78, respectively, indicating an acceptable internal reliability[48].

The KIDSCREEN-10 HRQoL score consists of ten self-reported items covering physical, psychological and social dimensions of well-being, with adolescents indicating the frequency or severity of each item on a 5-point Likert scale (1 = never/not at all, 2 = almost never/slightly, 3 = sometimes/moderately, 4 = almost always/very and 5 = always/extremely). Totals of these ten items were summed, with higher values indicating better HRQoL. Rasch person parameters were assigned to each possible total on the basis of the Rasch model, a psychometric model commonly used for measurements of categorical data[49]. The Rasch-scaled single score of HRQoL was then transformed into scores with a mean of 50 and an s.d. of approximately 10, where a higher score indicates a better HRQoL (Fig. 1d)[49]. The Cronbach's α for the KIDSCREEN-10 Questionnaire in our first and second visit samples was 0.75 and 0.78, respectively, indicating an acceptable internal reliability[48]. In line with previous studies, binary cut-offs were applied on the basis of the lower 10% of the sample distribution (t_0 and t_1 mean below 39.28 and 36.51, respectively) to identify adolescents with noticeably low overall well-being (two levels: 0 = high overall well-being and 1 = low overall well-being)[50]. All data on adolescents' cognitive development, mental health and overall well-being were gathered using Psytools software (Delosis Ltd.).

Quantification of natural-environment composition. Our exposure assessment of urban natural environments was based on a three-tier stepwise characterization: M I, natural space; M II, green versus blue space; M III, grassland versus woodland. We used different data sources to quantify the natural environments surrounding the residential and school areas of each adolescent. First, we generated an NDVI spatial layer of our study area using data from the Sentinel-2 satellite at 10 m spatial resolution[51]. NDVI is a unitless index of relative overall vegetation density and quality based on differential surface reflectance in the red and near-infrared regions[52]. It ranges between −1 and 1; generally, moderate values (0.2–0.3) represent shrubs and grassland, while high values (0.6–0.8) indicate temperate and tropical rain forests[52]. In our study, we used NDVI values >0.2 to identify vegetated areas as green space. We generated our NDVI layer by using Google Earth Engine to filter out satellite data between 1 July 2015 and 1 July 2017 for images with less-severe cloud cover (<5%)[53]. Images covering the same area at different dates were then mosaicked into a single complete and cloud-free image of NDVI (Supplementary Fig. 4a). Second, we created a spatial layer from surface- and tidal-water maps to quantify blue space in our study based on the Ordnance Survey (OS) Open Map, a large-scale digital map covering Great Britain (Supplementary Fig. 4b)[54].

To further assess fine-scale natural-environment types within green space, we used LiDAR data from the Environment Agency (data.gov.uk, accessed 2 July 2018, licensed under the Open Government Licence 3.0) (Supplementary Fig. 4c)[55]. We used the LiDAR Composite Digital Surface Model and Digital Terrain Model at 2 m spatial resolution to estimate object height across our study area. Within green space, we split vegetation into two height strata: 0−1 m and >1 m, where we assumed that vegetation between 0 and 1 m was predominantly grassland and vegetation, and vegetation >1 m was woodland[55].

We calculated each adolescents' proportionate DER to each natural-environment characterization in buffer areas of 50 m, 100 m, 250 m and 500 m around the residential and school areas:

$$\mathrm{DER} = \frac{\left(\frac{4\mathrm{RER}+8\mathrm{SER}}{12}\right)5 + 2\mathrm{RER}}{7} \tag{1}$$

where DER is the daily exposure rate, RER is the residential exposure rate and SER is the school exposure rate. We assumed each adolescent spent the weekend in their residential area, while we weighted weekdays by the daytime (12 hours) adolescents were assumed to spend at home (4 hours) and at school (8 hours). Adolescents who moved residence between the first and second visit had different DERs during t_0 and t_1. We selected different buffer areas to assess the consistency of our results in a comparable manner with previous studies[6,7,18]. On the basis of the preceding formula, we calculated natural-space DER by converting and merging our NVDI and water layers into a combined raster layer. Then, we calculated green- and blue-space DERs by using our NDVI and water layers separately. Finally, we calculated grassland and woodland DERs by combining our NDVI and height strata layers. The different spatial resolutions of our NDVI and height strata layers resulted in classification errors where pixels were misclassified as grassland or woodland when in fact they were part of the built environment. To correct for this, we excluded buildings from these layers using the buildings feature from OS Open Map (Supplementary Fig. 4d)[54]. It was not possible to use the blue-space DER of the 3,568 participants because 2,383 adolescents (66.8%) had, for example, no blue space within 250 m. We therefore reclassified blue space into tertiles (three levels: level 1, no blue space; level 2, blue space with a DER below the mean; level 3, blue space with a DER above the mean).

Quantification of outdoor air pollution. Considering the ability of nature to mitigate local air pollution[56], we hypothesized that exposure to air pollution could be an underlying confounder between nature exposure and cognitive development[57]. We did not hypothesize this for our mental-health and well-being outcomes because studies on the association between air pollution and these outcomes are still inconclusive[58,59]. We based our exposure assessment of air pollution on emission estimates of key air pollutants using the London Atmospheric Emission Inventory (LAEI) 2016 from GLA and Transport for London (data.london.gov.uk, accessed 27 February 2020, licensed under the UK Open Government Licence 2.0). The LAEI estimated ground-level concentrations of four air pollutants (nitrogen dioxide (NO_2), nitrogen oxides (NO_x), and particulate matter with a diameter of 10 microns or less (PM_{10}) or 2.5 microns or less ($PM_{2.5}$)) using an atmospheric dispersion model and covered Greater London as well as areas outside Greater London up to the M25 motorway. A total of 3,305 adolescents (out of 3,568 adolescents) were located within the M25 motorway and therefore eligible to measure ambient air pollution. Similar to the characterization of natural-environment types, we calculated each adolescent's average DER to each air pollutant in buffer areas of 50 m, 100 m, 250 m and 500 m around the residential and school areas following equation (1). The Pearson's correlation coefficient among DERs ranged from 0.95 (between NO_2 and PM_{10}) to 0.98 (between NO_2 and NO_x) (Supplementary Table 7). To avoid multicollinearity, we used NO_2 DER as it is a commonly used proxy for traffic-related air pollution.

Statistical analyses. Our modelling framework consisted of Bayesian longitudinal regression models to account for spatial and temporal correlations. We examined the relationship between natural-environment-type DERs and our cognitive-development, mental-health and overall well-being outcomes. Inference was performed using integrated nested Laplace approximation[60]. The Pearson's correlation coefficient among natural-environment DERs ranged from 0.38 (between grassland and woodland) to 0.99 (between natural space and green space) (Supplementary Table 1). The high Pearson's correlation coefficient was not considered a problem because we performed separated analyses for the different DERs. In particular, we developed three multilevel modelling structures including these as fixed effects, where M I included natural-space DER, M II included green- and blue-space DERs, and M III included grassland and woodland DERs. Our outcomes consisted of two repeated measures per adolescent: a t_0 and a t_1 measure. We assumed a Gaussian, Poisson and Binomial distribution for the EF score, SDQ total difficulties score and HRQoL score, respectively. We included a random effect term for adolescent identifier to allow for between-adolescent variance, while we used a random effect term for tests at the time of visit (two levels: first or second visit) for each adolescent to introduce correlation among the repeated measurements. School was not added as an additional random effect in our multilevel model because it did not improve the model fit, and three different cross-validation techniques were used for model comparison and selection (Supplementary Tables 8, 9 and 10). We explored the possibility of including a spatial effect, but residual analysis of our fully adjusted models indicated that the data were not spatially clustered using the Moran's I test (Supplementary Table 11). Fully adjusted models included natural-environment-type DERs, age, area-level deprivation, ethnicity, gender, parental occupation and school type, and models with the EF score were additionally adjusted for air pollution. In addition, we did a stratified analysis to investigate potential changes in point estimates and avoid potential bias from over adjustment (four levels: unadjusted, adjusted for ethnicity and school type, adjusted for socioeconomic factors and adjusted for all factors) (Supplementary Figs. 1, 2 and 3). A detailed description of the model structures is given in Supplementary Methods 1. Before the longitudinal analysis, a cross-sectional analysis of the cohort during the first visit was done, which was qualitatively similar to the longitudinal results and is therefore not further discussed (Supplementary Methods 2 and Supplementary Fig. 5).

We performed the following sensitivity analyses to determine the best models for evaluating the association with natural-environment-type DER by fitting additional Bayesian mixed-effect models for (1) the association with different buffer areas (Supplementary Figs. 1, 2 and 3) and (2) the association with a different weighting of natural-environment-type DERs based on a full-day (24 hours) instead of a daytime (12 hours) weighting where we assumed adolescents spend 16 hours at home and 8 hours at school during the weekdays (Supplementary Tables 2, 3 and 4). In the main text, unless stated otherwise, results were based on fully adjusted models with natural-environment-type DERs with a daytime weighting and measured in buffer areas of 250 m because we found no strong difference when measuring at different buffer areas or between daytime and full-day weighting. We did all data processing and statistics in Python 3.7.3., ArcGIS 10.7 and R 4.0.0 via RStudio using the packages brinla, ggplot2, ggpubr, R-INLA, MBA, raster, rgdal, sp and spdep[63].

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

Study population and environmental exposure data around each adolescent's residence and school are not publicly available for data protection issues. To request access to the data, contact M.B.T. Environmental data at the basis of our environmental exposure data are available at github.com/MikaelMaes/HumanExposure.git. The environmental data are based on publicly available sources. Sentinel-2 satellite data are available using Google Earth Engine at earthengine.google.com. Buildings, surface-water and tidal-water layers from the OS Open Map are available at ordnancesurvey.co.uk. LiDAR data from the Environment Agency are available at data.gov.uk. Air pollution estimates using the LAEI 2016 from GLA and Transport for London are available at data.london.gov.uk. The full model outputs that support the findings of this study are available in the Supplementary Information.

Code availability

The source code to compute our NDVI layer from satellite data using Google Earth Engine is available at earthengine.google.com. The code for processing raw LiDAR data, creating our environmental exposure variables and modelling our data is available at github.com/MikaelMaes/HumanExposure.git.

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Author contributions

M.J.A.M., K.E.J. and M.B.T. conceived the study and analysed the results. E.R.B. provided data on cognitive development. M.J.A.M. coded the models, performed the simulations and wrote the manuscript with substantial contributions from all the authors.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	The open source code to compute Normalised Difference Vegetation Index values from satellite data using Google Earth Engine is available at earthengine.google.com.
Data analysis	The code used to process raw LiDAR data using Python 3.7.3., creating our environmental exposure variables and modelling our data is available at github.com/MikaelMaes/HumanExposure.git.

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Identifiable study population data and environmental exposure data around each child’s home and school are not publicly available for data protection issues but anonymised datasets are available upon request. To request access to the data, contact M. B. Toledano at m.toledano@imperial.ac.uk. Environmental data that are the basis for our environmental exposure data are available at github.com/MikaelMaes/HumanExposure.git. This environmental data are based on publicly available sources. Sentinel-2 satellite data are available using Google Earth Engine at earthengine.google.com. Buildings, surface water and tidal water data from the Ordnance Survey Open Map are available at ordnancesurvey.co.uk. Light Detection and Ranging data from the Environment Agency are available at data.gov.uk. The air pollution estimates using the London Atmospheric Emission Inventory 2016 from the Greater London Authority and Transport for London are available at data.london.gov.uk. The full model outputs that support the findings of this study are available in the Supplementary Information.

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We use quantitative data from the Study of Cognition, Adolescents and Mobile Phones, a longitudinal cohort study established to investigate how the cognitive development, behaviour and well-being of children across the London metropolitan area during late childhood and early adolescence might be affected by use of mobile phones and other technologies that use radio waves. For more information, visit scampstudy.org.
Research sample	Initially, 6,612 children participated to the baseline assessment between 2014 and 2016, and 5,208 children participated to the follow-up assessment between 2016 and 2018. A total of 3,791 children participated to both the baseline and follow-up assessment, and for our analysis we used a subset of 3,568 children who had a known home address during the baseline and follow-up assessment. Included children were on average 12 and 14.2 years old during the baseline and follow-up assessment respectively, and 57.9% of them were female. The children (n = 3,568) were part of 31 schools across London, of which 12 were independent schools and 19 were state schools. Of the 31 participating schools, 3 were located outside the Greater London Authority administrative area. During the assessments, information was gathered on age, gender (two levels: female or male), ethnicity (five levels: White, Black, Asian, mixed or other), school type (two levels: state or independent), parental occupation (five levels: managerial/professional occupations, intermediate occupations, small employers/own account workers, lower supervisory/technical occupations or semi-routine/routine occupations), and area-level deprivation (divided in quintiles ranging from category 1 ‘least deprived’ to category 5 ‘most deprived’). Area-level deprivation was based on the Carstairs deprivation index to identify socioeconomic confounding. The scores were standardised to the area in which the child lived and not to the child itself in order to reflect the material deprivation of the area in relation to neighbouring areas. It is measured based on four variables from the United kingdom (UK) Office of National Statistics 2011 Census: proportion of low social class, lack of car ownership, household overcrowding and male unemployment. Further characteristics of the study population are presented in the Supplementary Information (Supplementary Table 6).
Sampling strategy	Eligible schools were selected from the Department of Education’s register of educational establishments (EduBase) and from the January 2012 school census. Both datasets include information on the type of school (e.g. independent school), pupil characteristics (e.g. sex), geographical location and pupil headcounts by school year or age. To select schools within the London Metropolitan area that have pupils in the target age range (11-12-year-olds), any school classified as a primary, infant, junior, or middle school or with a statutory minimum age of 12years was excluded. Any school classified as a special school, pupil referral unit or secure unit was also excluded as not representative of the general school-age population. Schools were included if they had a total Year 7 headcount of N >200 or N>50 pupils, for state and independent schools respectively. 206 eligible schools in Inner and Outer London were identified and mailed invitations to take part in SCAMP and 39 schools agreed to participate. In our subset study, only children with a known home address at baseline and follow up were included in the sample which totalled 3,568 children from 31 schools.
Data collection	Children's demographic and socio-economic information, cognitive development and mental health were assessed through self-reported data collection on computers in the classroom of each participating school. Besides the children and the researcher, also the teacher for each class was present during the baseline and follow-up assessment to ensure children were quiet and undertook the assessment under exam conditions. Children’s cognitive development was assessed through a composite measure of Executive Function, comprising three computerised tests (i.e. Backward Digit Span, Spatial Working Memory and Trail Making Task). We assessed children’s mental health from the self-reported Strength and Difficulties Questionnaire (SDQ) and the KIDSCREEN-10 Questionnaire taken by each child on the computer. The SDQ assesses the emotion and behaviour of children and consists of five subscales on emotional symptoms, conduct problems, hyperactivity/inattention, peer problems and prosocial behaviour. Each subscale comprises of five items that can be scored 0, 1 or 2 and each subscale score can therefore range from 0 to 10. The KIDSCREEN-10 questionnaire consists of 10 self-reported items covering physical, psychological and social dimensions of well-being, with children indicating the frequency or severity of each item on a 5 point Likert scale (1 = never/not at all, 2 = almost never/slightly, 3 = sometimes/moderately, 4 = almost always/very and 5 = always/extremely).
Timing	A baseline and follow-up school visit were carried out between 2014 and 2018 with a time gap of approximately 2 years between the baseline and follow-up visit for each school.
Data exclusions	We excluded children without a known home address at baseline and follow up as well as 8 schools due to low sampling sizes (< 15 children per school), resulting in our subset of 3,568 children.
Non-participation	Children could voluntarily drop out / decline participation during the baseline and follow-up assessment. Absenteeism on the day of the data collection in the school, also resulted in non-participation. All parents or guardians of participating children signed the informed consent.
Randomization	Children were not allocated into experimental groups.

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☒	☐ MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	See above
Recruitment	Recruitment was based on those schools which decided to take part in the Study of Cognition, Adolescents and Mobile Phones (see above, Sampling Strategy). Therefore, there was no selection bias at the individual level, because children were not recruited individually. Of the 39 participating schools in the main study, less than 0.5% of children's parents refused permission for their child to take part in the data collection.
Ethics oversight	The study was approved by the Health Research Authority NKES Committee North West - Haydock (Research Ethics Committees reference: 14/NW/0347).

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