Benefit of natural environments particularly woodland on adolescent's cognition and mental health

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ABSTRACT

Life in urban areas is associated with various human health effects, including risks of developing cognitive problems and mental health issues. Epidemiological studies have established associations between urban nature, cognitive development and mental health, but why specifically we receive these health benefits remains unclear, especially in adolescents. Here, we used longitudinal data in a cohort of 3,568 adolescents aged 9 to 15 years at 31 schools across London to develop a model and examine the associations between natural environment types, including green and blue space, and adolescent's cognitive development, mental health and overall well-being. We show that, after adjusting for other environmental, demographic and socio-economic variables, higher daily exposure rates to natural space and particularly woodland were associated with enhanced cognitive development and mental health during adolescence. Our results suggest that optimising ecosystem services linked to cognitive development and mental health benefits should prioritise the type of natural environment for sustainable urban planning decisions.

The past decades have seen a tremendous population growth in urban environments and is linked to a number of various human health effects[1,2], including risks of developing cognitive problems and mental health issues[3,4]. The negative effects of the COVID-19 pandemic has further exacerbated mental health problems[5,6], highlighting the importance to understand the dynamic interactions attributed to higher risk of cognitive problems and mental health issues in urban areas, which until now remain unclear. Emerging evidence suggests that exposure to natural environments plays an important role for cognitive development and mental health[7–9]. 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 urbanisation, and lower than parent's socio-economic status[8]. Sensory and non-sensory pathways have been suggested as potentially important for delivering cognition and mental health benefits received from nature exposure[10–15]. Further research into these pathways will prove fundamentally important to establish a mechanistic pathway between nature and mental health.

One of the barriers to understanding associations between natural environments, cognitive development and mental health is the use of inconsistent exposure definitions. Nature exposure has been measured, amongst others, as physical access to nature[16], natural environment type[17,18], nature dose[19] and degree of urbanisation[8,19]. 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 unit-less index of relative overall vegetation density and quality[7–9,20]. NDVI tends to simplify 'greenness' without taking into account the types of natural environment that exist. However, standing and flowing water bodies such as lakes, rivers or reservoirs (hereinafter called blue space) have been associated with mental health and cognitive development[20,21]. Similarly, forest has been proposed to generate a more restorative effect both psychologically[18,22] and physiologically[14], showing that forests have a more restorative effect when compared with overall urban green space, agricultural land or wetland, amongst others[18,22]. To date, there is no comprehensive analysis or agreement which measure of environmental exposure is more or less important.

Many studies have often focused on adult assessments of exposures to natural environments in relation to mental health[23]. There is growing recognition of the importance of adolescent's cognitive development and mental health, who are in the midst of their cognitive and mental development[24]. In fact, 1 in 10 of London's children and adolescents (~111,600 persons) between the ages of 5 and 16 suffer from a clinical mental health illness and excess costs are estimated between £11,030 and £59,130 annually for each person[24]. As for adults, there is evidence that natural environments play an important role in children and adolescent's cognitive development and mental health into adulthood[8,9,25]. However, many of these studies tend to exclude or simplify particular types of natural environment. Nonetheless, particular natural environment types such as blue space or woodlands have been suggested to influence children and adolescent's mental health[20,26], but to date it remains unclear what types of natural environment, if any, influence adolescent's cognitive development and mental health.

Study design. In this study, we developed a set of models estimating the contribution of natural environment types to adolescent's cognitive development and mental health and argue our findings can be used to inform future urban planning decisions. Our models demonstrated the benefit of urban natural environments and particularly woodland for cognitive development and mental health in adolescents. We focused our analysis on a longitudinal dataset of 3,568 adolescents from the Study of Cognition, Adolescents and Mobile Phones (SCAMP) across the London metropolitan area in the United Kingdom (Fig. 1a, Table 1 and Methods). We assessed cognitive development through a composite executive function (EF) score using computerised tests (Fig. 1b), while we assessed mental health through self-reported questionnaires on emotional and behavioural problems using the Strength 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). Higher EF scores indicated better cognitive performance, while a higher SDQ total difficulties score and HRQoL score 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 characterisation of natural environments: (Model I [M I]) natural space, (Model II [M II]) green vs. blue space, and (Model III [M III]) grassland vs. woodland. Grassland and woodland were characterised as green space lower and higher than 1 m, respectively. Our models identified an important protective factor for adolescent's cognitive development and mental health and we suggest that this can assist urban planners and decision-makers to sustainably manage urban nature. 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).

The impact of natural environment type on our outcomes. We estimated the change in adolescent's cognitive development, mental health and overall well-being for each type of natural environment by fitting our longitudinal models (Supplementary Methods 1). We found that adolescent's cognitive development improved with higher DER to natural space. When comparing those adolescents exposed to the highest level of natural space (~0.92%) to those exposed to the lowest level of natural space (~0.1%), we estimated a percent change in cognitive development of 2.14% (95% credible interval [CI]: 0.42, 4.29) using the EF score (Fig. 2a and Supplementary Figure 1a). We also provide the results for the SDQ total difficulties score and HRQoL score with natural space DER (Fig. 2b,c and Supplementary Figure 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 M I results for natural space DER. This is probably due to a high correlation between our DER for natural space and green space since adolescent's DER to blue space was generally low (Supplementary Table 1). This also meant that our models did not find an improvement of adolescent's cognitive development, mental health and overall well-being with DER of blue space (Fig. 2 and Supplementary Figure 2).

To further assess the role of different types of natural environment to adolescent's cognitive development, mental health and overall well-being, we characterised green space into two distinct natural environment types, i.e. 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 Figure 3). We found no improvement of overall well-being with higher DER to woodland (Fig. 2c and Supplementary Figure 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 percent change in cognitive development of 6.83% (95% CI: 3.41, 9.11) using the EF score, and a percent 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 adolescent's 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 Figure 3).

The role of other factors for our outcomes. We fitted our longitudinal models with a number of other factors to account for demographic, environmental and socio-economic factors that are known to influence adolescent's cognitive development and mental health [27,28]. We found that our outcomes for adolescent's 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 Table 2,3,4). When compared to independent schools for example, state schools were predicted to result in a negative contribution to adolescent's cognitive development, mental health and overall well-being by a percent change decrease 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 adolescent's cognitive development in some but not all models using the EF score (Supplementary Table 2). When removing demographic, environmental, and socio-economic factors from our models, we showed that modelled environmental variables were, in general, tenfold smaller than the contribution of our demographic and socio-economic variables (Supplementary Table 5). This stepwise exclusion of fixed effects from our models highlights the relative importance of our demographic and socio-economic variables to adolescent's 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 adolescent's cognitive development, mental health and overall well-being. This included testing each adolescent's DER for (i) different buffer areas around their residence and school and (ii) 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 Figure

1,2,3). 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 Table 2,3,4).

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 results showed a strong association between woodland exposure, and adolescent's cognitive development and mental health. We also found that exposure to natural space or 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.

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[14,18,29], with the exception of a study performed in central Scotland[30]. 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[14,29]. However, the hypothetical mechanisms why we experience these psychological benefits from woodland remain unknown. Higher audio-visual exposure through vegetation and animal abundance has been documented to improve mental health, of which both features are expected in higher abundance in woodland[12,31]. Even though our results show that urban woodland is associated with adolescent's cognitive development and mental health, the mechanistic pathway to explain this association remains unknown.

Our results also showed that exposure to natural space or green space was associated with a beneficial contribution to adolescent's cognitive development, which was consistent with previous studies[9,32]. Our findings of weaker associations between mental health and overall well-being outcomes with exposure to natural space or green space is consistent with the variability in these relationships found in previous studies[7,8,16,33]. It may be that most studies, including this study, do not account for the quality of green space, which has been proposed as more important than the quantity of green space[34]. Nevertheless, systematic reviews suggest that nature positively influences mental health; even though, evidence is often limited to cross-sectional studies, and inadequate particularly for adolescents[23].

We did not find a consistent association between blue space exposure, and our outcomes. However, we cannot dismiss that blue space may be associated with our outcomes as other studies have found associations[20,35]. In our study, 66.8% of participants had no blue space within 250 m, showing that the amount of blue space surrounding adolescent's residence and school was low regardless. One explanation for this weak association may be the changing composition of natural environments from one place to the other, potentially changing a person's attachment to nature[36]. Residents in coastal cities, for example, may have a different relationship with blue space compared to cities inland where blue space may be less abundant[37]. 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[20,35]. 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 harmonisation of nature exposure data.

Our findings suggested a stronger association with larger buffer areas when compared to smaller buffer areas, indicating that natural environments further away may play an important role for adolescent's cognitive development and mental health. This contrasts with the hypothesis that immediate surroundings may be more relevant for mechanisms of psychological restoration[20], and raises questions on the role of urban 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[38,39]. Further research to resolve this critical knowledge gap may prove fundamentally important to understand the pathway through which adolescent's receive cognitive development and mental health benefits from nature exposure.

The study has several strengths. It used a high-quality cohort dataset that, to our knowledge, is the largest epidemiological study to report on the impact of natural environment types on adolescent's cognitive development, mental health and overall well-being, a subset of the urban population which is often understudied. 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 adolescent's cognitive development, mental health and overall well-being. Previous studies have used satellite remote-sensing data for establishing associations between green space, 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 characterising 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, socio-economic status and other individual-level factors.

Despite of our large sample size using a rigorous longitudinal study design, our results could be influenced by a number of potentially confounding factors. For example, we cannot necessarily assume that adolescent's DER to natural environments leads to increased use of natural environments as the quality of natural environments may also play a role[20,34]. 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. We also showed that modelled environmental factors were, in general, tenfold smaller than the contribution of other factors, indicating that increasing nature exposure may not be sufficient to improve adolescent's cognitive development and mental health. Additionally, a considerable proportion of our participants (58.21%) were considered part of the group whose parents had the highest professional occupation, indicating adolescents in less favourable socio-economic groups may be underrepresented in this study (Supplementary Table 6). Added to this, unmeasured factors such as crime rates may also influence our results[40]. We also wanted our study to be generalisable to the majority of schools in the UK, but we do not exclude that pupils attending special schools, pupil referrals and secure units may be differently affected compared to the general school-age population of the UK. Finally, although our study importantly sheds light on the role of natural environment types for cognitive development and mental health, it also highlights the gap in understanding the mechanistic pathway why we receive benefits from woodland over other natural environment types.

CONCLUSION

Our study showed that higher levels of woodland were associated with a beneficial contribution to cognitive development and a lower risk of emotional and behavioural problems during adolescence. These findings contribute to our understanding of urban natural environment as an important protective factor for adolescent's cognitive development and mental health. Ensuring fair and equitable access to woodland could be an important tool to manage and minimise cognitive development and mental health problems, especially in adolescents who are in the midst of their development into adulthood. Lower access to woodland may also be an added risk factor among more vulnerable groups in society. Our findings contribute to our understanding of the physical and monetary valuation of cognitive development and mental health benefits received from urban nature, suggesting that not every natural environment type may contribute equally to these health benefits. As part of the growing human health and nature research, our study concludes that understanding people's local relationship with nature may be a key component to understand its association with cognitive development and mental health. This should be considered as part of ongoing efforts to sustainably develop urban nature and to standardise international measurement and environmental accounting frameworks for cognitive development and mental health benefits.

METHODS

Study population. We use data from SCAMP[41], 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 2 years between the first and second visit 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, Table 1). Out of these 3,568 adolescents, 607 (~17%) moved residence between the first and second visit. This subset excluded 8 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)[42], and area-level deprivation (divided in 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 socio-economic confounding[43]. 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[44]. We categorised 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 (REC reference: 14/NW/0347) by the Health Research Authority NKES Committee North West - Haydock. Study population data are not publicly available for data protection issues. To request access to the data, contact M. B. Toledano at m.toledano@imperial.ac.uk.

Outcomes. Adolescent’s cognitive development was assessed through a composite score of three computerised EF tasks (i.e. Backward Digit Span [BDS], Spatial Working Memory [SWM] and Trail Making Task [TMT])[45–47]. Versions of these tasks are widely used in EF literature. EF composite was only calculated 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[48]. 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 SD from the t_0 performance. Z-scores and adjusted values were calculated across the whole population at each time point. TMT and SWM values were reverse coded prior to taking the average. EF values were continuous and higher EF values indicated better cognitive performance (Fig. 1b).

We assessed adolescent's mental health and overall well-being from the self-reported SDQ and the KIDSCREEN-10 Questionnaire taken by each adolescent[49]. 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 comprised of 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)[49]. The Cronbach's α for the SDQ in our first and second visit sample was 0.79 and 0.78, respectively, indicating an acceptable internal reliability[50].

The KIDSCREEN-10 HRQoL score consists of 10 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 10 items were summed with higher values indicating better HRQoL. Rasch person parameters were assigned to each possible total based on the Rasch model, a psychometric model commonly used for measurements of categorical data[51]. The Rasch-scaled single score of HRQoL was then transformed into scores with a mean of 50 and a standard deviation of approximately 10, where a higher score indicates a better HRQoL (Fig. 1d)[51]. The Cronbach's α for the KIDSCREEN-10 Questionnaire in our first and second visit sample was 0.75 and 0.78, respectively, indicating an acceptable internal reliability[50]. In line with previous studies, binary cut-offs were applied based on the lower 10% of the sample distribution (i.e. 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)[52]. All data on adolescent's cognitive development, mental health and overall well-being were gathered using Psytools software (Delosis Ltd., London).

Quantification of natural environment composition. Our exposure assessment of urban natural environment was based on a three-tier stepwise characterisation: (M I) natural space, (M II) green vs. blue space, and (M III) grassland vs. woodland. We used different data sources to quantify the natural environment surrounding the residential and school area of each adolescent. Firstly, we generated a NDVI spatial layer of our study area using data from the Sentinel-2 satellite at 10 m spatial resolution[53]. NDVI is a unit-less index of relative overall vegetation density and quality based on differential surface reflectance in the red and near infrared regions[54]. 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 rainforests[54]. 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 July 1st 2015 and July 1st 2017 for images with less severe cloud cover (<5%)[55]. Images covering the same area at different dates were then mosaicked into a single complete and cloud-free image of NDVI (Supplementary Figure 4a). Secondly, 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 Figure 4b)[56].

To further assess fine-scale natural environment types within green space, we used LiDAR data from the Environment Agency (data.gov.uk, accessed July 2nd 2018, licensed under the Open Government Licence 3.0) (Supplementary Figure 4c)[57]. 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 - 1 m was predominantly grassland, and vegetation >1 m was woodland[57].

We calculated each adolescent's proportionate DER to each natural environment characterisation in buffer areas of 50 m, 100 m, 250 m and 500 m around the residential and school area:

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

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 a different DER 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[8,9,20]. Based on the above 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 DER by using our NDVI and water layers separately. Finally, we calculated grassland and woodland DER 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 it was part of the built environment. To correct for this, we excluded buildings from these layers using the buildings feature from OS Open Map (Supplementary Figure 4d)[56]. It was not possible to use 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, and 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[58], we hypothesised that exposure to air pollution could be an underlying confounder between nature exposure and cognitive development[59]. We did not hypothesise this for our mental health and well-being outcomes because studies on the association between air pollution and these outcomes are still inconclusive[60,61]. 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 February 27th 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 characterisation 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 area 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 (INLA)[62]. 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 DER, and M III included grassland and woodland DER. Our outcomes consisted of two repeated measures per adolescent, i.e. a t_0 and 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 Table 8,9,10). We explored the possibility to include a spatial effect, but residual analysis of our fully adjusted models indicated that the data was 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. Additionally, 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 socio-economic factors and adjusted for all factors) (Supplementary

Figure 1,2,3). A detailed description of the model structures is given in Supplementary Methods 1. Prior to 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 Figure 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 (i) the association with different buffer areas (Supplementary Figure 1,2,3) and (ii) 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 Table 2,3,4). 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, and between daytime or 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].

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. Toledano at m.toledano@imperial.ac.uk.

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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ACKNOWLEDGEMENTS

We thank Professor Marta Blangiardo (Imperial College London) and Dr Rory Gibb (University College London) for feedback on the statistical analyses. This study is supported by funding of the London Natural Environment Research Council Doctoral Training Program (NE/L002485/1), the MRC Centre for Environment and Health (MR/L01341X/1) based at Imperial College London and the NIHR Health Protection Research Unit in the Health Impact of Environmental Hazards, based at King's College London and Imperial College London, in partnership with Public Health England (PHE) (HPRU-2012-10141). SCAMP is independent research funded by the National Institute for Health Research (NIHR) Policy Research Program (PRP) (Secondary School Cohort Study of Mobile Phone Use and Neurocognitive and Behavioural Outcomes/091/0212) via the Research Initiative on Health and Mobile Telecommunications, a partnership between public funders and the mobile phone industry. An extension to SCAMP is funded by NIHR PRP. The funders of the study had no role in the design or conduct of the study nor the reporting of the SCAMP study results. M.B.T. chair and the work in this paper is supported in part by a donation from Marit Mohn to Imperial College London to support Population Child Health. The views expressed in this paper are those of the authors and not necessarily those of the NIHR, DHSC, PHE or any other funder.

AUTHOR CONTRIBUTIONS

M.J.A.M., K.E.J. and M.T.B. conceived the study and analysed the results. E.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.

FIGURES

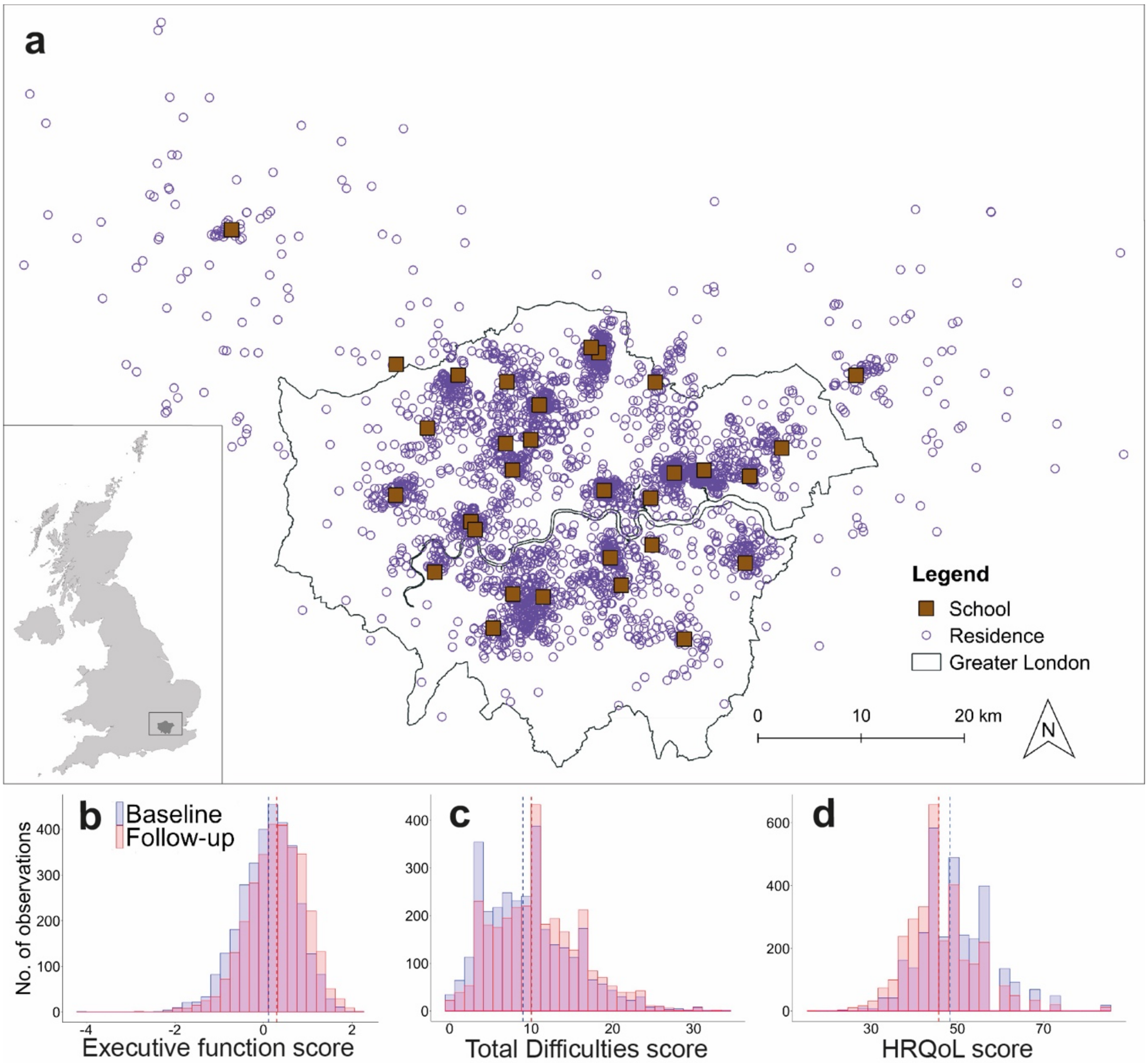

Fig. 1. Geographic distribution of our study population and associated health variables for cognitive development, mental health and overall well-being. (a) Residential location during the second (t_1) visit of the 3,568 adolescents with a known residence during the first (t_0) and second visit of the Study of Cognition, Adolescents and Mobile Phones and the 31 participating schools across the London metropolitan area, United Kingdom. Histograms show our t_0 (blue) and t_1 (red) outcome for cognitive development: (b) Executive function score, and our outcomes for mental health and overall well-being: (c) Strengths and Difficulties Questionnaire total difficulties score and (d) KIDSCREEN-10 Questionnaire Health-Related Quality of Life score. A dashed line marks the median (Q_1-Q_3) for our t_0 and t_1 outcomes, i.e. for (b) t_0: 0.16 (-0.30, 0.56), t_1: 0.33 (-0.10, 0.76), (c) t_0: 9 (6, 13), t_1: 10 (7, 14) and (d) t_0: 48.28 (43.34, 53.10), t_1: 45.66 (41.23, 49.76).

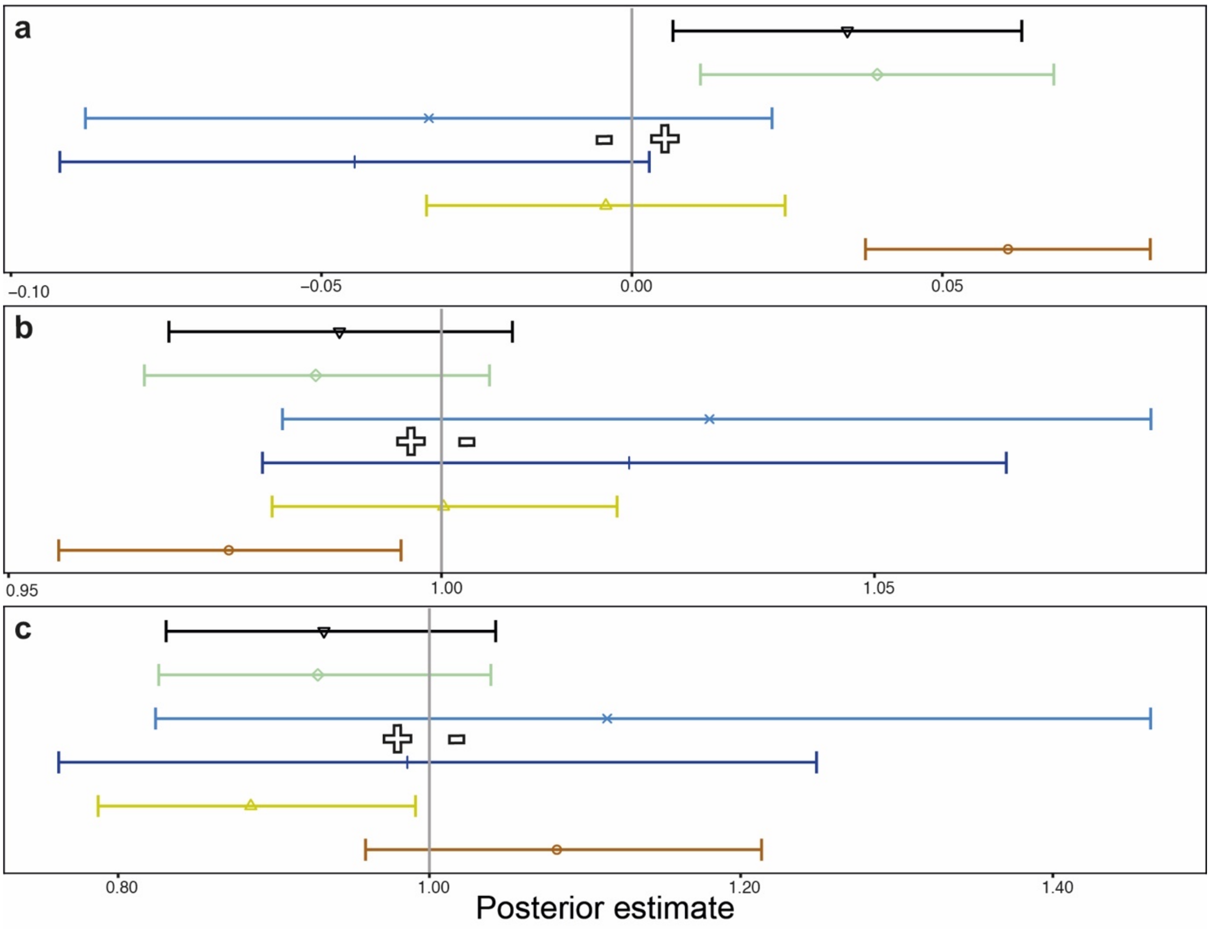

Fig. 2. Effects and 95% credible intervals (CI) of natural environment type daily exposure rate (DER) with cognitive development, mental health and overall well-being across London. The association between (a) executive function (EF) score, (b) Strengths and Difficulties Questionnaire total difficulties score and (c) KIDSCREEN-10 Questionnaire Health-Related Quality of Life score with the natural environment type DER of Model I: natural space (), Model II: green space (), blue space level 2 () and blue space level 3 (), and Model III: grassland () and woodland (). Blue space DER was reclassified into tertiles because 2,383 adolescents (~66.8%) had no blue space within 250 m (Methods). Fully adjusted model was plotted with posterior mean and 95% CI and included age, area-level deprivation, ethnicity, gender, parental occupation and school type. Models with EF as the outcome were additionally adjusted for air pollution. 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 indicated whether the association had a positive or negative contribution towards high cognitive development / good mental health vs. low cognitive development / poor mental health.

TABLES

Table 1. Cohort characteristics of the 3,568 adolescents with a known residence during the first (t_0) and second (t_1) school visit. 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 (NS-SEC) level (five-group version) of either parent. Qn1, Qn2, Qn3, Qn4 and Qn5 of area-level deprivation represented the first, second, third, fourth and fifth quintile of the Carstairs deprivation index, respectively. Full cohort characteristics during t_0 and t_1 are available in **Error! Reference source not found.**.

	n = 3,568	
	Median	IQR
Age (years)	12.96	12.02-14.22
Parental occupation	*n*	%
Managerial/professional occupations	2077	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)	1058	29.65
Missing	2	0.05
Gender		
Female	2069	57.98
Male	1499	42.01
Ethnicity		
White	1617	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	2556	71.63
Independent	1012	28.36