Exposure to woodland and other natural environments and educational achievement in urban adolescents: mechanistic insights from the SCAMP cohort study

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**Exposure to woodland and other natural environments and educational achievement in urban adolescents: mechanistic insights from the SCAMP cohort study**

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**Abstract**

**Background**
Exposure to urban nature, especially woodland, is associated with better cognitive function and mental health in adolescents. However, it remains unclear how exposure to the natural environment contributes to educational achievement. We examined the longitudinal associations between exposure to natural-environment-type and adolescents' educational achievement, including the mediation effects of cognitive function, behavioural difficulties, and air pollution.

**Methods**
We analysed longitudinal data (n=5323) from a large, representative Greater London adolescent cohort study (SCAMP). Natural environment types were characterised by greenspace and blue space at 11-12 years. Greenspace was further distinguished into woodland and grassland. Educational achievement at 16 years was based on the General Certificate of Secondary Education (GCSE) via record linkage. Cognitive function (executive function and fluid intelligence), behavioural difficulties, and air pollution measured/modelled at 11-12 years were included as mediators. Data were analysed using multi-level linear regression model and multi-level mediation analysis.

**Results**
Higher exposure to greenspace was associated with higher GCSE maths grades. Higher exposure to woodland, but not grassland, was associated with higher GCSE maths, science, and English grades. Executive function and fluid intelligence partially mediated the associations between woodland exposure and GCSE grades (12.5% to 25.1% of associations mediated). The mediation effects of behavioural difficulties or air pollution were not evident.

**Conclusions**
Our findings provide evidence to inform urban planning by showing the associations between different types of natural environments and educational achievement. These findings also offer important insights for creating healthy equitable cities for children and adolescents to live in.

**Keywords**
Greenspace, Woodland, Educational achievement, Adolescents, Cognitive function, Urban planning

## 1. Introduction

Urban populations have grown exponentially in recent decades, with 68% of the global population expected to live in urban areas by 2050 (United Nations, 2018). Adolescence represents a sensitive period of brain development which may provide a greater window for environmental influences compared to other developmental stages (Fuhrmann et al., 2015). Epidemiological research has indicated greater exposure to natural environments in urban areas (e.g., greenspace, blue space, woodland) is associated with better cognitive development, health, and wellbeing in children and adolescents (Amoly et al., 2014; Maes et al., 2021; Ye et al., 2022). Educational achievement (e.g., successful completion of compulsory education) is associated with an individual's career prospects and life expectancy (Ingleby et al., 2021). Lower educational achievement is also associated with an increased risk of cardiovascular disease, depression, and smoking behaviour (Gilman et al., 2008; Kubota et al., 2017; Peyrot et al., 2015).

There has been a growing interest in understanding the relationship between natural environments and educational achievement, but findings have been mixed. The majority of research to date is based on ecological study designs using aggregated data e.g., greenspace coverage within or surrounding schools and school-level educational achievement via standardised test scores (Browning & Rigolon, 2019; Davis et al., 2021). Some studies have found that greater school greenspace and tree cover have been associated with better school-level performance in academic tests such as maths, reading, and spelling (Browning & Locke, 2020; Claesen et al., 2021; Kuo et al., 2018; Leung et al., 2019; Li et al., 2019), but other studies have shown an inverse association (Beere & Kingham, 2017; Browning et al., 2018). However, inference from these ecological studies is limited due to residual confounding, ecological fallacy, and the lack of estimates of exposure to residential natural environments. Few studies have used individual-level data on exposure estimates and outcomes to examine the associations between natural environments and educational achievement in children and adolescents. Those that exist are subject to methodological limitations (e.g., recall bias due to self-reported educational achievement (Markevych et al., 2019; Singh et al., 2023), using dichotomous educational variables (Ahmed et al., 2022), or a lack of differentiation between types of natural environments (Garkov et al., 2025)). These limitations raise the importance of further studies to yield more robust evidence for urban planning.

Exposure to the natural environment might benefit educational achievement via several plausible pathways. Natural environments, including green and blue spaces, may contribute to cognitive restoration and stress recovery, building capacities for physical activity and social cohesion, and reducing air pollution and noise exposure (Britton et al., 2020; Markevych et al., 2017). These factors may also shape educational achievement. Our previous research showed that adolescents living in greener urban environments, especially with more woodland exposure, display greater executive function ability and fewer behavioural difficulties (Maes et al., 2021), which both correlate with academic achievement (Samuels et al., 2016; Smith et al., 2021). Additionally, greater coverage of natural environments also reduces exposure to air pollution, which has been linked to impairments in structural brain development (Lopuszanska & Samardakiewicz, 2020; Thompson et al., 2024). However, no studies have formally investigated these pathways. Such mechanistic evidence strengthens causal inference and enables a better understanding of how the natural environment can benefit educational achievement.

This study aims to investigate the longitudinal associations between individual-level exposure to different types of natural environments and educational achievement in a large-scale longitudinal cohort study (the Study of Cognition, Adolescents, and Mobile Phones (SCAMP)). We also aim to examine the mediation effects of cognitive function, behavioural difficulties, and air pollution on these associations, to generate mechanistic insights.

## 2. Methods

### 2.1 Participants

SCAMP is a prospective school-based adolescent cohort study across Greater London, UK. Details of this cohort have been reported elsewhere (Toledano et al., 2019). The geographic distribution of SCAMP participants and schools is shown in Figure 1. Baseline data were collected from 6590 School Year 7 pupils (aged 11-12 years) from 39 secondary schools (26 state and 13 independent) between November 2014 and July 2016 (T1). Of these participants, 3814 from 31 schools participated in the follow-up data collection when they were in School Year 9/10 (aged 13-15 years) between November 2016 and July 2018 (T2). Participants completed a computer-based assessment administered by Psytools software (Delosis Ltd) in examination conditions. The assessment included a battery of cognitive tasks and detailed questionnaires on digital technology behaviours, mental health scales, physical health, lifestyle (e.g., sleep, smoking, alcohol use), and demographic characteristics.

The North-West Haydock Research Ethics Committee approved the SCAMP study protocol and subsequent amendments (ref 14/NW/0347). School head teachers consented to participation in SCAMP. Participants were provided in advance with written information about the study and were given the opportunity to opt out of the research at any time. The study was conducted in accordance with the Declaration of Helsinki.

**2.2 Exposure - natural environment estimates (T1)**

Natural environment estimates at T1 were included as the exposure variables. We quantified individual-level exposure to different types of natural environments surrounding residence and school areas for SCAMP participants. Specifically, greenspace was quantified based on the Normalized Difference Vegetation Index (NDVI) layer, generated using Google Earth Engine and Sentinel-2 satellite data. We identified the vegetated area as greenspace if the NDVI value was greater than 0.2 (Gascon et al., 2016). Blue space was quantified based on the water layer, generated by the Ordnance Survey (OS) Open Map. Total nature space was quantified by merging NDVI and water layers into a combined raster layer. To further characterise different types of greenspaces, we used the LiDAR Composite Digital Surface Model and Digital Terrain Model to estimate object height within greenspace across our study area. We defined woodland as vegetation height greater than 1m, and grassland as vegetation height between 0 and 1m (Miura & Jones, 2010). Exposure to woodland and grassland is missing in a small proportion of participants (4.8%), given that LiDAR data are not available in their residence or school areas. We calculated the daytime (12h) daily exposure rate (DER) for each type of natural environment in 50m, 100m, 250m, and 500m buffer areas surrounding their homes and schools. We assumed that participants spend 8 hours at school and 4 hours at home on weekdays and spend the entire weekend in their residential area. Details of exposure estimates are shown elsewhere (Maes et al., 2021).

$$Daytime\ DER = \frac{\left(\frac{exposure_{school} * 8 + exposure_{home} * 4}{12}\right) * 5 + exposure_{home} * 2}{7}$$

We used the natural-environment-type DERs with daytime weighting in a 250m buffer area in our main analyses unless stated otherwise, in line with our previous work (Maes et al., 2021). We used the 250m buffer as our main spatial resolution of exposures as it reflects the neighbourhood environment that is accessible and suitable for walking as part of adolescents' daily routines. Daytime weighted DER reflects exposure to natural environments during waking time when adolescents are most likely to experience potential cognitive and psychological benefits associated with visual exposure. The distribution of natural-environment-type in Greater London is shown in Figure S1.

**2.3 Outcome - educational achievement at age 16 (T3)**

Educational achievement for SCAMP participants was obtained via data linkage to the National Pupil Database (NPD), supplied by the UK Department for Education (Department of Education, 2024). Educational data were available for SCAMP participants with successful record linkage, regardless of participation in data collection at T2. In England, pupils aged 16 years take their

General Certificate of Secondary Education (GCSE) examinations (Key Stage 4) as the completion of compulsory secondary education. We included the highest grades achieved in individual GCSE core subjects: maths, science, and English language as our outcomes. GCSE grades range from 1 to 9, with 9 being the highest. SCAMP participants took GCSEs in academic years 2018-2019 and 2019-2020.

**2.4 Mediators - Cognitive function, behavioural difficulties, and air pollution (T1)**

*2.4.1 Cognitive function*

Executive function and fluid intelligence were included. Executive function was assessed by the average standardised z-score from three individual tasks, the Trail Making Task (TMT) (Tombaugh, 2004), Backwards Digit Span (BDS) task (Dumontheil & Klingberg, 2012), and Spatial Working Memory (SWM) task (Luciana & Nelson, 2002). TMT measures cognitive flexibility, whilst BDS and SWM measure working memory. TMT and SWM values were reverse-coded prior to taking the average so that a higher score indicates better performance on all tasks.

Fluid intelligence was measured by the Cattell Culture Fair Task (CFT), a standard visuospatial reasoning test (Cattell, 1949). The total number of correct trials on the two subtasks (the Odd One Out task and the Complete the Pattern task) reflects non-verbal reasoning and is a proxy for non-verbal fluid intelligence. A higher number indicates better non-verbal fluid intelligence. We excluded participants who completed only one subtask.

*2.4.2 Behavioural difficulties*

Behavioural difficulties were measured using the Strengths and Difficulties Questionnaire (SDQ), a widely used screening measure of socioemotional skills in children and adolescents (Goodman, 2001). A total difficulties score was computed by summing the relevant items for four subscales (emotional problems, conduct problems, peer problems, and hyperactivity). The Cronbach's α for the total SDQ score was 0.79, indicating acceptable internal consistency (Cronbach, 1951).

*2.4.3 Air pollution*

Outdoor $NO_2$, $PM_{2.5}$, $PM_{10}$, and ozone exposures (all in μg/m$^3$) were included as mediators given their associations with greenspace and cognition (Thompson et al., 2024; Venter et al., 2024). Annual individual-level estimates for SCAMP participants were modelled using the CMAQ-urban at a spatial resolution of 20m*20m. CMAQ-urban is a high-resolution model integrating emissions inventories, road transport, meteorological data, and a chemical scheme (Beevers et al., 2012). We used the average exposure estimates between 2014 and 2016 (reflecting the T1 assessment period) in the mediation model.

**2.5 Covariates**

Sociodemographic information includes age, gender, ethnicity, socioeconomic classification of parents, parental education, and area-level deprivation. Ethnicity was categorised as "White", "Black", "Asian", and "Other". Parental socioeconomic status (SES) was derived based on the Office for National Statistics classification of occupation, categorising it into three levels ("Managerial and professional", "Intermediate", and "Routine or manual"). If these differed between parents, participants were assigned the higher parental SES. Parental education was categorised in a binary form as follows: at least one parent with higher education versus no parents with higher education. Area-level deprivation was assessed based on the Index of Multiple Deprivation (IMD) in 2015 derived from the postcode of residential addresses at baseline. IMD is a weighted average score of seven domains of deprivation, including income, employment, education, health, crime, barriers to housing and services, and living environment. IMD was divided into quintiles, ranging from 1 "most deprived" to 5 "least deprived" (https://imd-by-postcode.opendatacommunities.org/imd/2015). Covariates also included Key Stage 2 grades of maths, science, reading, and writing, obtained via record linkage to NPD. Primary school students in England take Key Stage 2 exams at ages 10-11 years.

**2.6 Statistical analysis**

Multi-level linear models were used to assess the associations between each natural-environment-type DER in a 250m buffer area and GCSE grades, taking into account school clustering effects. Total natural space, greenspace, woodland, and grassland DER were analysed as continuous variables (i.e., per interquartile (IQR) increase) to maximise the statistical power to detect associations with GCSE grades. As most SCAMP participants (67.5%) had no blue space in a 250m buffer, the distribution of blue space DER was zero-inflated. Analysing it as a continuous variable may yield a poor model fit. Therefore, we categorised blue space DER into three groups (none, mean or lower, above the mean). Model 1 adjusted for the respective Key Stage 2 grades only. Model 2 (the main model) additionally adjusted for sociodemographic covariates (age, gender, ethnicity, parental SES, and area-level deprivation). We did not adjust for parental education in the main analysis due to the high proportion of missing data.

Multi-level mediation analysis was used to assess the mediation effects of cognitive function, behavioural difficulties, and air pollution on the associations between natural-environment-type DER and GCSE grades. Indirect effect, direct effect, total effect, and proportion of mediation for individual mediators were derived from mediation analysis. We used the product-of-coefficients method to calculate the indirect effects (MacKinnon et al., 2007). Specifically, we derived the product of the coefficient for the association between exposure and mediator (model a) and the coefficient for the association between mediator and outcome adjusting for exposure (model b). The same covariates (e.g., age, gender, ethnicity, socioeconomic classification of parent, area-level deprivation, and Key Stage 2 grades) were adjusted for in both models. We performed mediation analyses only if there was a statistically significant association between a natural-environment-type exposure and an educational achievement outcome. The 95% confidence intervals for mediation analysis were estimated using a bootstrap procedure with 500 bootstrap replications.

We performed a series of sensitivity analyses (SA) to test the robustness of our findings. **SA1:** We assessed the associations between natural-environment-type DER in different buffer sizes (50m, 100m, and 500m) and educational achievement. **SA2:** We further adjusted for parental education and native language (English versus non-English). **SA3:** We used multiple imputation to predict missing data on woodland and grassland exposures, ethnicity, parental SES, IMD, and Key Stage 2 grades (the proportion of missingness ranged between 2.7% and 11.1%) by chained equations. Total natural space, greenspace, and blue space DER in different buffer areas (50m, 100m, 250m, and 500m), GCSE grades, age, gender, and school were included in the imputation model. We imputed 20 datasets and then summarised the results from 20 imputed datasets into single estimates with 95% CIs adjusted for missing data uncertainty. **SA4:** We assessed the associations between full-day (24h) weighted natural-environment-type DER (instead of daytime (12h) exposure) and GCSE grades based on the assumption that adolescents spend 16 hours at home and 8 hours at school on weekdays and 24h in their residential area on weekends. **SA5:** We excluded participants whose GCSE grades were obtained in the academic year 2019/2020. These grades were based on teacher assessment due to the COVID-19 pandemic, rather than on exams as in previous years, and may not be directly comparable. **SA6:** We excluded participants who moved home at T2 (n=602) to address the potential non-differential misclassification due to change in exposures. **SA7:** We used sequential causal mediation analysis using g-computation to investigate the mediation effects of cognitive function and behavioural difficulties at T1 and T2 on the associations between natural environments and educational achievement (VanderWeele & Vansteelandt, 2014; Wang & Arah, 2015). This approach accounts for time-varying mediators to assess longitudinal mediation effects. **SA8:** We investigated the mediation effects of specific behavioural difficulties using SDQ subscale scores on the associations between natural-environment-type DER and GCSE grades. All data processing and analyses were performed using STATA (version 16.0), R (version 4.0.3), and QGIS (version 3.36.2).

**2.7 Public and Community Involvement, Engagement and Participation (PCIEP)**
This work is part of the SCAMP Research Challenge programme, launched in October 2022. The SCAMP Research Challenge is an innovative approach to PCIEP, encouraging young people to get involved in scientific research. We have trained 170 Research Challenge students across 19

secondary schools to design and pitch their own research questions using SCAMP data, and to support data collection fieldwork in their schools (not analysed in this study). Research Challenge students from Alec Reed Academy (https://www.alecreedacademy.co.uk/) proposed investigating how time spent outdoors and digital technology use affect executive function in adolescents. Their research proposal was refined under the guidance of SCAMP researchers to formulate research questions answered in this study.

## 3. Results

Participants with linked data on environmental exposure at T1 and at least one measure of educational achievement at T3 were included in the present analysis (n=5323). Table 1 shows that the mean age at baseline was 11.63 years (standard deviation = 0.48). More than half (54.0%) of participants were female. The sample was diverse in terms of ethnicity, parental SES, and area-level deprivation. Blue space DER was lower than greenspace DER. Woodland DER was lower than grassland DER.

Table 2 shows that in the fully adjusted model (Model 2), per IQR increases in total natural space, greenspace, and woodland DER were associated with higher GCSE maths grades (0.23 points higher per IQR increase in all three DER). Per IQR increase in woodland DER was also associated with higher GCSE science grades of 0.23 points (95% CI 0.07, 0.39) and higher English language grades of 0.21 points (95% CI 0.08, 0.34). Per IQR increase in grassland DER was associated with lower GCSE English language grades of -0.15 points (95% CI -0.28, -0.02). Blue space DER was not associated with GCSE grades. To aid interpretation, we translated effect estimates to the differences in GCSE grades between participants with the 90$^{th}$ percentile woodland DER and those with the 10$^{th}$ percentile DER. Participants with the 90$^{th}$ percentile woodland DER had 0.43 points (95% CI 0.21, 0.65) higher in GCSE maths grades, 0.43 points (95% CI 0.13, 0.74) higher in science grades, and 0.40 points (95% CI 0.16, 0.64) higher in English language grades than participants with the 10$^{th}$ percentile DER.

Mediation analysis (Tables 3 and 4) shows that EF and fluid intelligence at T1 partially mediated the associations between woodland DER and GCSE maths, science, and English language grades with statistically significant indirect effects. The proportion of mediation ranged between 12.5% and 25.1%. The mediation effects of behavioural difficulties (Table 3) and air pollution (Table 4) on natural-environment-type DER and GCSE grades were not significant.

Our results were consistent across different buffer areas (50m, 100m, 500m), although the magnitudes of some associations varied slightly (SA1) (Table S1, Figure S2). The associations between total natural space and greenspace DER and GCSE science grades became significant in 50m and 100m buffers, although the association magnitudes varied little. Total natural space and greenspace DER across buffer areas were consistently associated with higher GCSE maths grades, but not with English language grades. Woodland DER in different buffer areas were consistently associated with higher GCSE maths and English language grades. Further adjustments for parental education and native language yielded similar results, although the association between total natural space and GCSE science grades became significant (SA2, Table S2). Multiple imputation on missing woodland and grassland exposures and covariates (SA3, Table S3) using the full-day weighting for DER (SA4, Table S4) did not alter the association pattern, although the association magnitudes slightly decreased. The association pattern also remained similar with slightly increased magnitudes when excluding participants whose GCSE grades were obtained during the COVID-19 pandemic (SA5, Table S5). The association pattern remained the same with similar magnitudes of associations after excluding participants who moved home at T2 (SA6, Table S6).

Table S7 shows the results of sequential mediation analysis (SA7) including cognitive function and behavioural difficulties at T1 and T2 as mediators. We found that fluid intelligence partially mediated the associations between total natural space and greenspace and GCSE maths grades with statistically significant indirect effects. The associations between woodland DER and GCSE maths, science, and English language grades were still partially mediated by executive function and fluid intelligence. The mediation effects of behavioural difficulties on natural-environment-type DER and GCSE grades were also not significant. Our results indicate that longitudinal mediation effects were generally consistent with the mediation effects observed when including mediators at T1 only. Table S8 shows the mediation analysis including scores of SDQ subscales as mediators (SA8). We found that conduct problems mediated a small proportion of the associations between total natural space and greenspace and GCSE maths grades (7.0% and 6.9%, respectively). Emotional problems, peer problems, and hyperactivity did not mediate the associations between natural-environment-type DER and GCSE grades.

## 4. Discussion

To our knowledge, this is the first epidemiological study in the UK to assess the longitudinal associations between different types of natural environments and individual-level educational achievement based on a national examination. We are also the first to investigate multifactorial pathways underlying these associations. Our study found that exposure to greenspace at ages 11-12 was associated with higher GCSE maths grades at age 16. Exposure to woodland, but not grassland, was associated with higher GCSE maths, science, and English language grades. The associations between woodland exposure and GCSE grades were partially explained by executive function and fluid intelligence, but not by behavioural difficulties or air pollution.

To date, few studies have investigated the associations between urban natural environments and subject-specific educational achievement in children and adolescents using individual-level data (Ahmed et al., 2022; Garkov et al., 2025; Markevych et al., 2019; Singh et al., 2023). Our findings for English grades are consistent with results from a longitudinal study in Germany (n=2429) which did not find associations between the combined residential and school greenspace exposures in a 500m buffer area (using a full-day weighting) and German grades in adolescents aged 10 and 15 years (Markevych et al., 2019). Another cross-sectional analysis in a Polish sample (n=658) did not find any association between residential or school greenspace or blue space exposures in a 500m buffer area and Polish grades in participants aged 10-13 years (Singh et al., 2023). However, our findings differ from these two studies, which did not show associations between greenspace or tree cover and maths grades. Another longitudinal study in Australian participants aged 10-12 years did not find an association between residential greenspace exposure in a 500m buffer and grades in reading, writing, language conventions, or numeracy scores under a national assessment program (Ahmed et al., 2022). However, that study did not consider school greenspace or further characterise greenspace into woodland or grassland. Our study has a larger sample size than these three studies, enabling greater power to detect significant associations. Moreover, these studies dichotomised educational achievement outcomes (instead of analysing them as a continuous variable), resulting in a loss of power to detect differences associated with exposures. In addition, information on educational achievement in two studies was self-reported by parents and pupils which could have introduced recall bias (Markevych et al., 2019; Singh et al., 2023).

Our study demonstrated longitudinal associations between higher exposure to greenspace, particularly woodland, and higher educational achievement. This aligns with another study showing that both the morphology and the quantity of greenspace are associated with children's mental health with comparable underlying pathways (Huang et al., 2025). Our associations remained evident after taking into account the influences of parental SES and neighbourhood deprivation. This indicates that access to greenspace and woodland during early adolescence may benefit future educational achievement independent of individual- and area-level socio-economic factors. We found that woodland exposure was associated with the grades of all three core subjects. Our mediation analysis suggests that woodland may confer broader benefits on educational achievement across subject domains through cognitive pathways. However, greenspace exposure was not associated with GCSE English language grades. It has been shown that measures of working memory (a key component of executive function) at age 15 are more strongly associated with GCSE maths and science grades than with English language grades (Donati et al., 2019). Our previous study found a weaker association between greenspace exposure and executive function compared with woodland exposure (Maes et al., 2021), therefore the benefits on executive function associated with greenspace exposure may be insufficient to translate into measurable differences in English language grades. Although our longitudinal design enables a temporal sequence of natural environment exposure, cognitive function, and educational outcomes, we cannot fully rule out the possibility of residual confounding. Particularly, genetically or socially influenced intelligence could affect both residential choice of parents and educational achievement of adolescents.

Notably, the associations between exposure to greenspace and woodland and educational achievement remained evident after adjusting for executive function or fluid intelligence (i.e., significant direct effect), suggesting other underlying mechanisms than cognitive function. While air pollution remains a significant factor for general respiratory health, none of the air pollution estimates investigated in our study mediated the associations between greenspace or woodland exposure and GCSE grades. This suggests that the reductions in air pollution exposure may not underlie the benefits of greenspace and woodland. Alternatively, access to greenspace may offer physiological and psychological benefits such as a reduced risk of obesity and mental restoration in children and adolescents (Ye et al., 2022). Obesity is a risk factor for poorer educational achievement (Booth et al., 2014). Mental restoration may alleviate mental fatigue during study and stimulate the ability to pay attention, which should contribute to enhanced educational achievement (Kaplan & Berman, 2010). Natural sound and biodiversity are key to mental restoration attributed to greenspace exposure, where both features are expected to be more prevalent in woodland environments (Irvine et al., 2009; Wood et al., 2018). This might explain the more pronounced associations observed in woodland exposure compared with grassland exposure. Moreover, in an urban environment, grassland cover may represent heterogeneous land use (e.g., park, derelict land) (Kowarik, 2011), which may have varied effects on educational achievement. However, we do not have the information on land use quality to distinguish these effects. Heterogeneity of usage may explain the null associations observed for grassland.

We did not find any association between blue space exposure and educational achievement. One plausible explanation is that participants living in London, an inland city, have generally low exposure to blue space. The low level of blue space exposure in our study may not be sufficient to yield the health benefits observed elsewhere with coastal proximity (Amoly et al., 2014; White et al., 2013). This is consistent with another study in an inland area of Poland which also did not find an association between blue space and maths or Polish grades (Singh et al., 2023).

This is a large-scale longitudinal cohort study with high-quality and detailed individual-level data on environmental exposures, cognitive and behavioural phenotyping, and educational achievement. This provides a unique opportunity to disentangle the associations between different types of natural environments surrounding residential and school areas and educational achievement as well as to investigate a range of plausible mechanisms underlying these associations. Educational achievement outcomes were obtained via record linkage instead of self-report, which minimises the concerns of cohort attrition and recall bias.

However, our study has limitations. Information on time spent in greenspace was available for only a small proportion of participants at baseline (n<800), so we are unable to comprehensively investigate its underlying role in the associations between greenspace access and educational achievement. Future research with more detailed and well-powered data on exposure dosage such as time spent and nature of use in greenspace could improve our understanding of the benefits of natural environment beyond passive exposure. We only considered baseline exposure to natural environments to maximise the sample size, and the proportion of participants who reported a different home address at follow-up was 15.8% (602/3814). However, the associations remained very similar after excluding this group, therefore the exposure misclassification is unlikely to bias our findings. Moreover, natural-environment-type DER remained similar for the majority of these participants (e.g., the absolute difference of greenspace DER in a 250m buffer area was <10% between baseline and follow-up for 71% (427/602) of these participants), suggesting that residential mobility would have limited influence on the findings. In addition, future research should investigate cumulative exposure and exposure during key developmental windows (e.g., early childhood) in relation to educational achievement, as sustained and earlier exposure to natural environments may demonstrate stronger associations with educational outcomes. The calculation of natural-environment-type DER was based on the assumption that participants spent all their non-school time in their residential areas without taking into account access to the natural environment encountered in other places. Evidence indicates the heterogeneity in the associations between greenspace and children's mental health by age and health status (Huang et al., 2025). Therefore, it is plausible that the associations observed in our study may differ across subgroups such as sex, deprivation, or baseline cognition.

Our study has the potential to generate sound recommendations for local governments and policymakers. Variations in associations between each natural-environment-type and GCSE grades may inform urban planning policy for decision-makers to balance natural and built environments as well as different types of natural environments, to optimise benefits of educational achievement in adolescents and ultimately benefit academic growth and the future success of urban populations. These environmental factors may perpetuate existing inequalities where certain populations have less access to greenspace and its benefits. Our findings suggest that greenspace is associated with educational achievement independent of area-level deprivation. Increasing greenspace in deprived urban areas may address inequalities in academic performance and its health and social implications. Specific urban planning interventions include enhancing tree canopy and developing small urban parks ("pocket park") with high tree-canopy density within walking distance of schools and homes (Nordh et al., 2009). Urban planning strategies could also consider school place planning, whereby new schools are located in close proximity to accessible greenspace. Educational achievement outcomes included here are the results of a national examination as the completion of compulsory secondary education. Our findings may inform future intervention studies to investigate the benefits of outdoor teaching/learning in nature, especially in places with greater woodland cover. Our study provides solid evidence in London, supporting the expansion and evolution of the UK National Education Nature Park programme launched in autumn 2023 (Hazell & Clarke, 2024).

Our study was conducted in Greater London, a highly urbanised and dense setting where exposure to natural environments, particularly woodland, is relatively scarce with marked spatial discrepancies. However, natural environments are more abundant and evenly accessible in less dense cities, towns, or rural areas in the UK (Ngan et al., 2025). Students attending schools outside London have poorer GCSE performance than those attending London schools (Department of Education, 2025). In addition, restoration that underlies the cognitive benefits of natural environments might be more prominent in highly urbanised areas (Vella-Brodrick & Gilowska, 2022). Therefore, the associations between natural environments and educational achievement including the underlying mechanisms may be contextually specific. A replication study, with mechanistic insights, in cities outside London and also less urbanised settings is warranted.

## 5. Conclusions

Our study found longitudinal associations between exposure to greenspace and higher GCSE maths grades in adolescents. Exposure to woodland, but not grassland, was associated with higher GCSE maths, science, and English language grades. Our findings suggest that adolescents in Greater London with high woodland exposure (e.g., 90$^{th}$ percentile) may achieve nearly half a GCSE grade higher on average than those with low woodland exposure (e.g., 10$^{th}$ percentile). Executive function and fluid intelligence, but not air pollution, partially mediated these associations. This pattern suggests that the associations between woodland and educational achievement may be more likely explained by cognitive benefits than by reductions in air pollution exposure. Our findings may inform urban planning by showing the associations between different natural-environment-types and educational achievement. These findings also offer important insights for creating healthy equitable cities for children and adolescents to live in.

**Data statement**

According to the terms of consent for SCAMP participants, access to individual-level SCAMP data needs to be approved by the SCAMP Data Access Committee (https://scampstudy.org/get-involved/opportunities-for-researchers/). Application should be made to scamp@imperial.ac.uk. The data dictionary is available on request to the corresponding author.

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Figure 1 Geographic distribution of SCAMP participants and schools

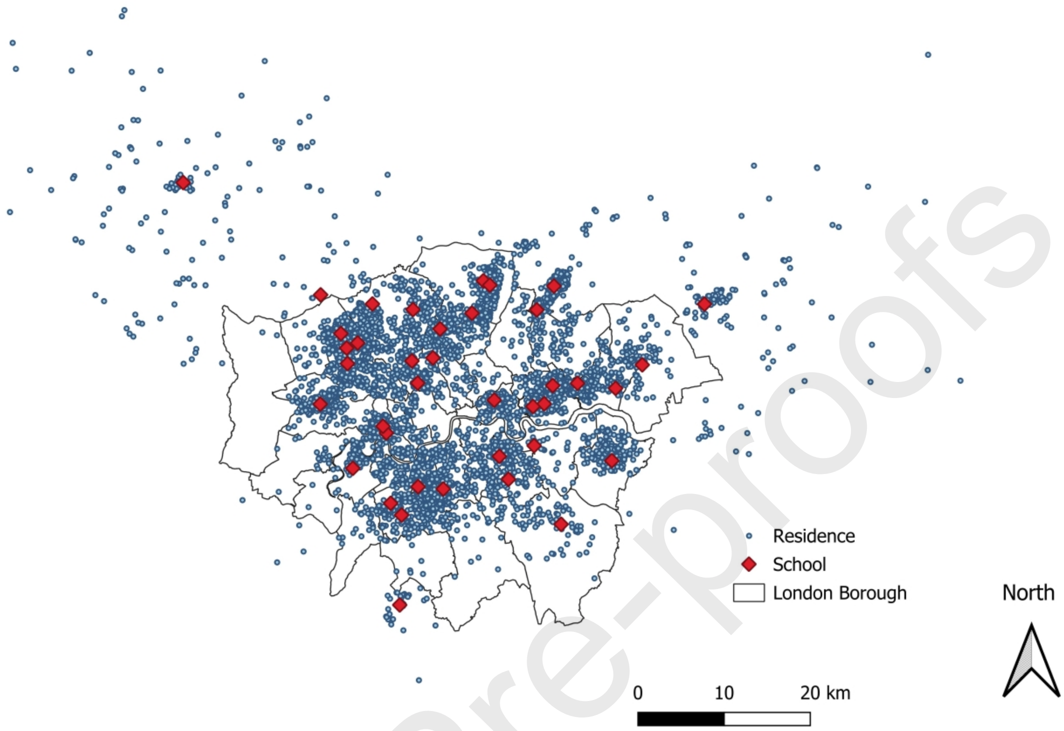


Table 1 Descriptive characteristics of the analytical sample (n=5323)

| | |
|---|---|
| **Demographic variables** | |
| Age, mean (SD) | 11.63 (0.48) |
| Gender, n (%) | |
| Male | 2449 (46.0) |
| Female | 2874 (54.0) |
| Ethnicity, n (%) | |
| White | 2177 (40.9) |
| Black | 542 (10.2) |
| Asian | 1517 (28.5) |
| Others/mixed | 944 (17.7) |
| Missing | 143 (2.7) |
| Parental socioeconomic status, n (%) | |
| Managerial/professional occupations | 2614 (49.1) |
| Intermediate occupations | 1182 (22.2) |
| Routine and manual occupations | 1032 (19.4) |
| Missing | 495 (9.3) |
| Parental education, n (%) | |
| At least one parent with higher education | 2821 (53.0) |
| No parent with higher education | 1078 (20.3) |
| Missing | 1424 (26.8) |
| Index of multiple deprivation in quintile, n (%) | |
| Qn1 (most deprived) | 1230 (23.1) |
| Qn2 | 1537 (28.9) |
| Qn3 | 1123 (21.1) |
| Qn4 | 792 (14.9) |
| Qn5 (least deprived) | 454 (8.5) |
| Missing | 187 (3.5) |
| First language, n (%) | |
| English | 3043 (57.2) |
| Non-English | 2263 (42.5) |
| Missing | 17 (0.3) |
| **Exposures** | |
| Total natural space DER (250m buffer), mean (SD) | 0.51 (0.17) |
| Greenspace DER (250m buffer), mean (SD) | 0.51 (0.17) |
| Blue space DER (250m buffer), n (%) | |
| None | 3594 (67.5) |
| Mean or lower | 908 (17.1) |
| Above the mean | 821 (15.4) |
| Woodland DER (250m buffer), mean (SD) | 0.08 (0.05) |
| Grassland DER (250m buffer), mean (SD) | 0.38 (0.13) |
| **Outcomes[a], mean (SD)** | |
| GCSE maths grade | 5.19 (2.04) |
| GCSE science grade | 5.44 (2.08) |
| GCSE English language grade | 5.27 (1.87) |

DER: daily exposure rate (based on daytime weighting); GCSE: General Certificate of Secondary Education; SD: standard deviation

a: GCSE grades range from 1 to 9 (with 9 being the highest)

Table 2 Associations between natural-environment-type daily exposure rates at T1 (250m buffer, daytime weighting) and GCSE maths, science, and English language grades

| Models | Exposure | IQR | Maths[c] | | Science[d] | | English[e] | |
|---|---|---|---|---|---|---|---|---|
| | | | n | b (95% CI) | n | b (95% CI) | n | b (95% CI) |
| Model 1 | Total natural space (per IQR increase) | 0.261 | 3849 | 0.27 (0.15, 0.40) | 3784 | 0.18 (0.01, 0.34) | 3896 | 0.02 (-0.11, 0.16) |
| | Greenspace[a] (per IQR increase) | 0.261 | 3849 | 0.28 (0.15, 0.40) | 3784 | 0.18 (0.02, 0.35) | 3896 | 0.04 (-0.10, 0.18) |
| | Blue space | | | | | | | |
| | None | - | 2599 | 0 (Reference) | 2570 | 0 (Reference) | 2620 | 0 (Reference) |
| | Mean or lower | - | 608 | -0.02 (-0.18, 0.14) | 588 | 0.07 (-0.12, 0.26) | 634 | -0.00 (-0.16, 0.16) |
| | Above the mean | - | 642 | 0.03 (-0.11, 0.16) | 626 | 0.00 (-0.16, 0.17) | 642 | -0.08 (-0.22, 0.06) |
| | Woodland[b] (per IQR increase) | 0.059 | 3683 | 0.30 (0.18, 0.41) | 3619 | 0.32 (0.16, 0.48) | 3730 | 0.28 (0.16, 0.41) |
| | Grassland (per IQR increase) | 0.193 | 3683 | 0.04 (-0.08, 0.16) | 3619 | -0.06 (-0.22, 0.10) | 3730 | -0.17 (-0.31, -0.04) |
| Model 2 | Total natural space (per IQR increase) | 0.261 | 3849 | 0.23 (0.11, 0.35) | 3784 | 0.13 (-0.03, 0.29) | 3896 | -0.02 (-0.16, 0.11) |
| | Greenspace (per IQR increase) | 0.261 | 3849 | 0.23 (0.10, 0.35) | 3784 | 0.14 (-0.03, 0.30) | 3896 | -0.01 (-0.14, 0.13) |
| | Blue space | | | | | | | |
| | None | - | 2599 | 0 (Reference) | 2570 | 0 (Reference) | 2620 | 0 (Reference) |
| | Mean or lower | - | 608 | -0.04 (-0.19, 0.12) | 588 | 0.05 (-0.14, 0.24) | 634 | -0.02 (-0.18, 0.13) |
| | Above the mean | - | 642 | 0.08 (-0.06, 0.21) | 626 | 0.06 (-0.10, 0.22) | 642 | -0.03 (-0.17, 0.11) |
| | Woodland (per IQR increase) | 0.059 | 3683 | 0.23 (0.11, 0.35) | 3619 | 0.23 (0.07, 0.39) | 3730 | 0.21 (0.08, 0.34) |
| | Grassland (per IQR increase) | 0.193 | 3683 | 0.06 (-0.06, 0.17) | 3619 | -0.03 (-0.19, 0.13) | 3730 | -0.15 (-0.28, -0.02) |

CI: confidence interval; IQR: interquartile range

Model 1: Adjusted for respective Key Stage 2 grades.

Model 2: Additionally adjusted for age, gender, ethnicity, parental socioeconomic status, and area-level deprivation.

School clustering effect was taken into account in both models.

a: greenspace and blue space were mutually adjusted in both models.

b: woodland and grassland were mutually adjusted in both models.

c: Key Stage 2 maths grade was adjusted in both models.

d: Key Stage 2 science grade was adjusted in both models.

e: Key Stage 2 writing and reading grades were adjusted in both models.

Table 3 Mediation effects of cognitive and behavioural measures at T1 on the associations between natural-environment-type daily exposure rates at T1 (250m buffer, daytime weighting) and GCSE maths, science, and English language grades

| Exposure (per IQR increase) | Mediator | Outcome | Indirect effect[c] | Direct effect | Total effect | Proportion mediated |
|---|---|---|---|---|---|---|
| | | | b (95% CI) | b (95% CI) | b (95% CI) | |
| Total natural space | Executive function | Maths | 0.02 (-0.00, 0.05) | 0.21 (0.10, 0.33) | 0.24 (0.12, 0.35) | - |
| Total natural space | Fluid intelligence | Maths | 0.02 (-0.00, 0.05) | 0.19 (0.07, 0.31) | 0.21 (0.09, 0.34) | - |
| Total natural space | Behavioural difficulties | Maths | 0.01 (-0.01, 0.02) | 0.24 (0.12, 0.35) | 0.24 (0.13, 0.36) | - |
| Greenspace[a] | Executive function | Maths | 0.02 (-0.00, 0.05) | 0.21 (0.09, 0.32) | 0.23 (0.11, 0.35) | - |
| Greenspace | Fluid intelligence | Maths | 0.03 (-0.00, 0.06) | 0.20 (0.08, 0.32) | 0.23 (0.10, 0.35) | - |
| Greenspace | Behavioural difficulties | Maths | 0.01 (-0.01, 0.02) | 0.24 (0.12, 0.35) | 0.24 (0.13, 0.36) | - |
| Woodland[b] | Executive function | Maths | 0.03 (0.01, 0.05) | 0.20 (0.10, 0.31) | 0.23 (0.13, 0.34) | 12.5% |
| Woodland | Fluid intelligence | Maths | 0.04 (0.02, 0.07) | 0.18 (0.07, 0.28) | 0.22 (0.11, 0.33) | 19.8% |
| Woodland | Behavioural difficulties | Maths | 0.00 (-0.01, 0.02) | 0.22 (0.11, 0.33) | 0.23 (0.12, 0.33) | - |
| Woodland | Executive function | Science | 0.05 (0.01, 0.08) | 0.18 (0.03, 0.33) | 0.22 (0.07, 0.38) | 20.5% |
| Woodland | Fluid intelligence | Science | 0.06 (0.03, 0.10) | 0.19 (0.04, 0.34) | 0.25 (0.11, 0.40) | 25.1% |
| Woodland | Behavioural difficulties | Science | 0.01 (-0.01, 0.02) | 0.21 (0.05, 0.36) | 0.21 (0.06, 0.37) | - |
| Woodland | Executive function | English | 0.03 (0.01, 0.05) | 0.17 (0.05, 0.30) | 0.20 (0.08, 0.33) | 14.6% |
| Woodland | Fluid intelligence | English | 0.04 (0.02, 0.05) | 0.18 (0.05, 0.30) | 0.21 (0.09, 0.33) | 16.6% |
| Woodland | Behavioural difficulties | English | 0.01 (-0.01, 0.02) | 0.20 (0.08, 0.32) | 0.20 (0.08, 0.32) | - |

CI: confidence interval; IQR: interquartile range

Adjusted for age, gender, ethnicity, parental socioeconomic status, area-level deprivation, and respective Key Stage 2 grades; School clustering effect was taken into account.

Mediation analyses were conducted only where there was a statistically significant association between a natural-environment-type exposure and an educational achievement outcome (see Model 2 in Table 2).

a: additionally adjusted for blue space.

b: additionally adjusted for grassland.

c: the indirect effects were calculated using the product of coefficients method, derived from the coefficient for the association between exposure and mediator and the coefficient for the association between mediator and outcome adjusting for exposure. The same covariates were adjusted for in both models.

Table 4 Mediation effects of air pollution at T1 on the associations between natural-environment-type daily exposure rates at T1 (250m buffer, daytime weighting) and GCSE maths, science, and English language grades

| Exposure (per IQR increase) | Mediator | Outcome | Indirect effect[c] | Direct effect | Total effect |
|---|---|---|---|---|---|
| | | | b (95% CI) | b (95% CI) | b (95% CI) |
| Total natural space | Ozone | Maths | -0.02 (-0.08, 0.03) | 0.27 (0.13, 0.42) | 0.25 (0.11, 0.38) |
| Total natural space | $PM_{2.5}$ | Maths | -0.03 (-0.09, 0.03) | 0.28 (0.13, 0.43) | 0.25 (0.12, 0.39) |
| Total natural space | $PM_{10}$ | Maths | -0.02 (-0.07, 0.03) | 0.27 (0.12, 0.42) | 0.25 (0.12, 0.39) |
| Total natural space | $NO_2$ | Maths | -0.02 (-0.07, 0.03) | 0.27 (0.12, 0.41) | 0.25 (0.11, 0.38) |
| Greenspace[a] | Ozone | Maths | -0.03 (-0.09, 0.03) | 0.28 (0.13, 0.42) | 0.25 (0.11, 0.39) |
| Greenspace | $PM_{2.5}$ | Maths | -0.03 (-0.09, 0.02) | 0.29 (0.13, 0.44) | 0.25 (0.12, 0.39) |
| Greenspace | $PM_{10}$ | Maths | -0.02 (-0.07, 0.03) | 0.27 (0.12, 0.42) | 0.25 (0.11, 0.39) |
| Greenspace | $NO_2$ | Maths | -0.02 (-0.08, 0.03) | 0.27 (0.12, 0.42) | 0.25 (0.11, 0.39) |
| Woodland[b] | Ozone | Maths | 0.00 (-0.01, 0.01) | 0.20 (0.06, 0.33) | 0.20 (0.06, 0.33) |
| Woodland | $PM_{2.5}$ | Maths | -0.00 (-0.00, 0.00) | 0.20 (0.06, 0.33) | 0.20 (0.06, 0.33) |
| Woodland | $PM_{10}$ | Maths | -0.00 (-0.00, 0.00) | 0.20 (0.06, 0.33) | 0.20 (0.06, 0.33) |
| Woodland | $NO_2$ | Maths | 0.00 (-0.01, 0.01) | 0.20 (0.06, 0.33) | 0.20 (0.06, 0.33) |
| Woodland | Ozone | Science | -0.00 (-0.01, 0.01) | 0.24 (0.08, 0.41) | 0.24 (0.08, 0.41) |
| Woodland | $PM_{2.5}$ | Science | 0.00 (-0.01, 0.01) | 0.24 (0.07, 0.40) | 0.24 (0.07, 0.40) |
| Woodland | $PM_{10}$ | Science | 0.00 (-0.01, 0.01) | 0.24 (0.07, 0.41) | 0.24 (0.07, 0.41) |
| Woodland | $NO_2$ | Science | -0.00 (-0.01, 0.01) | 0.24 (0.08, 0.41) | 0.24 (0.07, 0.41) |
| Woodland | Ozone | English | -0.00 (-0.01, 0.01) | 0.22 (0.08, 0.37) | 0.22 (0.08, 0.36) |
| Woodland | $PM_{2.5}$ | English | 0.00 (-0.01, 0.01) | 0.22 (0.08, 0.36) | 0.22 (0.08, 0.36) |
| Woodland | $PM_{10}$ | English | 0.00 (-0.01, 0.01) | 0.22 (0.08, 0.36) | 0.22 (0.08, 0.36) |
| Woodland | $NO_2$ | English | -0.00 (-0.01, 0.00) | 0.23 (0.08, 0.37) | 0.22 (0.08, 0.36) |

CI: confidence interval; IQR: interquartile range

Adjusted for age, gender, ethnicity, parental socioeconomic status, area-level deprivation, and respective Key Stage 2 grades; School clustering effect was taken into account.

Mediation analyses were conducted only where there was a statistically significant association between a natural-environment-type exposure and an educational achievement outcome (see Model 2 in Table 2).

a: additionally adjusted for blue space.

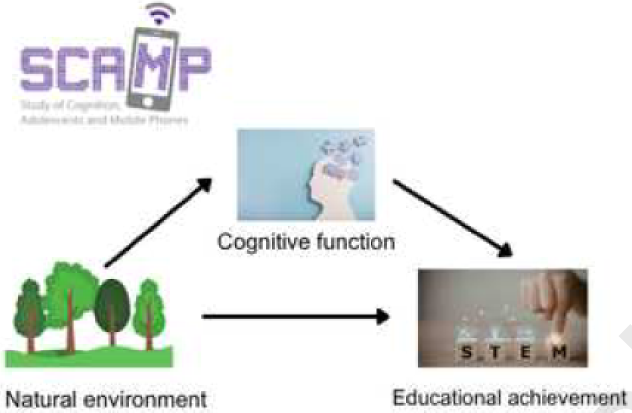
b: additionally adjusted for grassland.

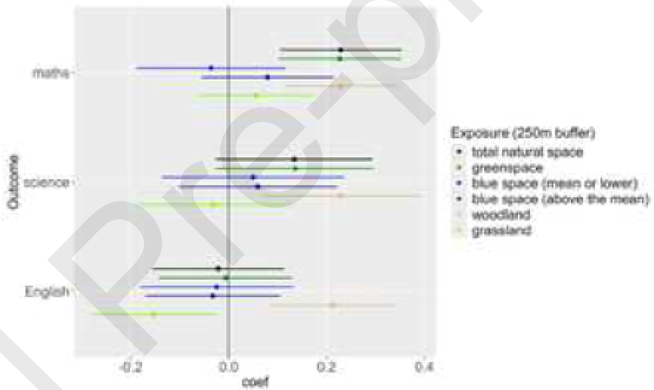
c: the indirect effects were calculated using the product of coefficients method, derived from the coefficient for the association between exposure and mediator and the coefficient for the association between mediator and outcome adjusting for exposure. The same covariates were adjusted for in both models.

Graphical Abstract



## Exposure to woodland and other natural environments and educational achievement in urban adolescents: mechanistic insights from the SCAMP cohort study




**Conclusions:** Our findings provide evidence to inform urban planning by showing the associations between different types of natural environments and educational achievement. These findings also offer important insights for creating healthy equitable cities for children and adolescents to live in.

Highlights

- Evidence has linked greenspace to better educational achievement in adolescents.
- The mechanism linking natural environment and educational achievement is unknown.
- Higher exposure to woodland, not grassland, was associated with higher GCSE grades.
- Cognitive function mediated the associations between woodland and GCSE grades.
- Our findings offer insights for creating healthy equitable cities for adolescents.

**Declaration of interests**

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

**Author contributions: CRediT**

**Chen Shen**: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing
**Nicole Curtis**: Methodology, Project administration, Writing – review & editing
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**Roisin C Perry**: Methodology, Writing – review & editing
**Rachel B Smith**: Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing – review & editing

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