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Title: Residential greenness and children's working memory. An EU Child Cohort Network consortium study.

AUTHOR ACCEPTED MANUSCRIPT

Authors: Mikel Subiza-Pérez[1,2,3,4*], Gonzalo García-Baquero[5], Marisa Rebagliato[3,6,7], Marisa Estarlich[3,7,8], Mónica Guxens[3,9,10,11,12], Martine Vrijheid[3,9,10], Montserrat de Castro [3,9,10], Mark Nieuwenhuijsen[3,9,10], Silvia Fernández[9,13], Jordi Sunyer[3,9,10,14], Jordi Julvez[3,10,15], Tim Cadman[10,16], Ahmed Elhakeem [17], Mark Mon-Williams[2,18], Liam Hill[18,19], Amanda Waterman[18,19], Ane Arregi[1,4], Nerea Lertxundi[1,3,4], Aitana Lertxundi[3,4,20].

[1] Department of Clinical and Health Psychology and Research Methods, University of the Basque Country UPV/EHU, Avenida Tolosa 70, Donostia-San Sebastián 20018, Spain
[2] Bradford Institute for Health Research, Temple Bank House, Bradford Royal Infirmary, Duckworth Lane, Bradford BD9 6RJ, UK
[3] Spanish Consortium for Research on Epidemiology and Public Health (CIBERESP), Instituto de Salud Carlos III, c/ Monforte de Lemos 3-5, Madrid 280, Spain
[4]Biogipuzkoa Health Research Institute, Group of Environmental Epidemiology and Child Development, Paseo Doctor Begiristain s/n, Donostia- San Sebastián 20014, Spain
[5]Faculty of Biology, University of Salamanca, Salamanca, Spain
[6]Predepartamental Unit of Medicine, Jaume I University, Castelló, Spain.
[7]Epidemiology and Environmental Health Joint Research Unit, FISABIO–Universitat Jaume I–Universitat de Valencia, Valencia, Spain.
[8]Faculty of Nursing and Chiropody, Universitat de Valencia, Valencia, Comunitat Valenciana, Spain
[9]ISGlobal, Barcelona, Spain
[10]Universitat Pompeu Fabra, Barcelona, Spain
[11]Department of Child and Adolescent Psychiatry/Psychology, Erasmus MC, University Medical Centre, Rotterdam, The Netherlands
[12] ICREA, Barcelona, Spain
[13]Agencia de Salut Pública de Barcelona, Pl. Lesseps 1, 08023 Barcelona, Spain
[14]IMIM (Hospital del Mar Medical Research Institute), Barcelona, Spain
[15]Clinical and Epidemiological Neuroscience (NeuroÈpia), Institut d'Investigació Sanitària Pere Virgili (IISPV), 43204 Reus, Spain.
[16]UMCG Genetics Department, University Medical Centre Groningen, Groningen, Netherlands
[17]Integrative Epidemiology Unit at the University of Bristol, Bristol, UK
[18]School of Psychology, The University of Leeds, LS2 9JT, Leeds, UK
[19]Centre for Applied Education Research, Wolfson Centre for Applied Health Research, Bradford, UK
[20] Department of Preventive Medicine and Public Health, University of the Basque Country (UPV/EHU), Leioa, Spain

* Corresponding author

Corresponding author information:
Mikel Subiza-Pérez, PhD.
Department of Clinical and Health Psychology and Research Methods, University of the Basque Country UPV/EHU, Avenida Tolosa 70, Donostia-San Sebastián 20018, Spain
mikel.subiza@ehu.eus

1. Introduction

Cognitive tasks such as language comprehension, learning, reasoning and problem-solving require the storage and management of information (Baddeley, 1992; Vuontela et al., 2003). One key executive function for these purposes is working memory (WM), which emerges from the interaction between memory and attention and allows an individual to store and manipulate information for short periods of time (Cowan, 2014; Shelton et al., 2010). Longitudinal studies on WM have shown that it improves during childhood before showing a period of latency in early adolescence (10 to 13 years; Ahmed et al., 2022; Reynolds et al., 2022). WM also shows a brief second period of improvement in middle adolescence (14 to 16 years).

Environmental epidemiologists and researchers in related disciplines have been working intensively during the past decade to map and quantify the potential salutogenic effects of green spaces and greenness on a wide range of health outcomes (Dzhambov et al., 2020; Markevych et al., 2017). One of the potential pathways for positive impact is the reduction of exposure to air pollutants because: (i) pollutants may become deposited on vegetated surfaces (Lindén et al., 2023); (ii) green spaces create an increased distance to emission sources such as roads (Klingberg et al., 2017). In this context, the study of whether higher exposure to residential green spaces and greenness leads to higher working memory scores has received considerable attention. A recently published systematic review (Buczyłowska et al., 2023) compiled the results of seven observational studies linking green space and greenness metrics with WM outcomes in participants of various ages between 4 and 18 years. Four of these studies showed statistically significant protective effects. The remaining three studies did not find any supporting evidence. In a more recent study, not included in the systematic review, marginally significant associations ($p < 0.10$) were found between both green space availability and residential Normalized Difference Vegetation Index (NDVI) and WM scores and in a sample of over 1,600 children aged 6 to 11 years living in various European cities (Fernandes et al., 2023).

In the present study, we wanted to contribute to the debate by analysing new data that could help clarify the associations, if any, between residential green spaces, greenness metricsand WM. In addition, we wished to explore the specific issue of WM and reduced exposure to NO_2, a pollutant that has been specifically linked to WM performance in childhood (Alemany et al., 2018; Forns et al., 2017; Sunyer et al., 2015).

2. *Methods*

2.1 Sample of participants

Data from participants in pregnancy cohorts included in the LifeCycle Project (Nader et al., 2023) was accessed. More specifically, we included data from those cohorts with available residential greenness metrics and WM data during childhood. From 19 participating cohorts, we requested data to Avon Longitudinal Study of Parents and Children (ALSPAC; Boyd et al., 2013; Fraser et al., 2013), Born in Bradford (BiB; McEachan et al., 2024; Wright et al., 2013) and the Gipuzkoa, Sabadell and Valencia Infancia y Medio Ambiente cohorts (INMA; Guxens et al., 2012) which were the only ones with available WM assessments. These cohorts provided data from children aged 10 to 12 years (ALSPAC), 7 to 10 years (BiB), 6 to 8 years and 10 to 12 years (INMA). Ethics and funding aspects of each cohort study are described in the supplementary materials.

2.2 Study variables

2.2.1 Exposures

The residential environment of each participant the year when the WM assessment was conducted was characterised via two complementary residential greenness metrics widely used in the field (Labib et al., 2020; Nordbø et al., 2018); NDVI and the availability of green spaces > 5,000 m^2. The NDVI is a greenness measure derived from satellite imagery. We used imagery corresponding to in the maximum vegetation period from the Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) with 30m x 30m resolution was used to determine the surrounding greenness. NDVI scores range from 1 to +1 (Tucker, 1979), with 1 being the maximum greenness level. Negative NDVI values correspond to water, snow and other non-vegetated surfaces and were removed to calculate the final scores (Peters et al., 2022; Zhang et al., 2020).

Availability of major (>5000 m^2) greenspace was computed using Urban Atlas. For ALSPAC and the INMA 6 to 8 years follow-up, we used the following land cover classes within Urban Atlas (Copernicus, 2006) : 14100 (Green urban areas), 30000 (Forests and semi-natural areas), and 20000 (Agricultural areas). In the case of BiB and INMA 10 to 12 years follow-up, a wider set of classes (Copernicus, 2012) were included: 14100 (Green urban areas), 21000 (Arable land [annual crops]), 22000 (Permanent crops), 23000 (Pastures), 24000 (Complex and mixed cultivation patterns), 25000 (Orchards), 31000 (Forests), and 32000 (Herbaceous vegetation associations).

Following previous studies (Binter et al., 2022; Nieuwenhuijsen et al., 2019), we used NDVI values expressed in radii of 100, 300 and 500 m. Finally, in line with the recommendations of the World Health Organization (WHO Regional Office for Europe, 2016), availability of green spaces was defined within 300 m of the participants' residence. More information about the procedure followed to calculate these variables can be found elsewhere (Fossati et al., 2019).

2.2.2 Mediator

Individual residential exposure to NO_2 also during the year of WM assessment was estimated using the land use regression (LUR) models. For ALSPAC, we resorted to the models created for the Effects of Low-Level Air Pollution: A Study in Europe project (ELAPSE; (De Hoogh et al., 2018). For BiB and INMA, we used the LUR models developed in the European Study of Cohorts for Air Pollution Effects (ESCAPE; Beelen et al., 2013; Estarlich et al., 2011). These models explained a high proportion of the observed variance in the NO_2 levels measured in the air pollution campaigns conducted to validate them (the following coefficients are R^2 scores); ALSPAC = 0.54, BiB = 0.77, INMA-Gipuzkoa = 0.51, INMA-Sabadell = 0.77, and INMA-Valencia = 0.73.

2.2.3 Outcome

Participants' WM performance was measured in each of the cohort and follow-ups included in the study. In ALSPAC and INMA (6 to 8 and 10 to 12 years), WM was measured with N-back tests, a computerized cognitive task consisting of the recall of a previously presented stimulus (i.e., number). The stimuli appeared on the screen one at a time, and the participant was instructed to press a button if the current stimulus was the same as the second to last stimulus shown (2-back test). A WM score was calculated via the estimation of the d prime (d') index, a measure derived from signal detection theory that allows the distinction of signal from noise. Measures of d' were calculated for each trial as follows: d' = z (hit rate) – z (false alarm rate), a higher d' indicating better detection, and thus, a more accurate performance (Deserno et al., 2012; Stanislaw, 1999). The task was created using the psychology experiment software E-Prime version 2.0 (Psychology Software Tools Inc, Pittsburgh, PA, USA).

In the case of BiB, WM memory was measured with the backward digit recall task. In this task, participants were requested to recall sets of numbers they heard through headphones and input in reverse order using keyboard keys (Hill et al., 2022). The length of the sets of numbers increased from two to five, with four trials per set. The overall WM score corresponded to the proportion of correct answers in all the trials.

Once these separate scores were calculated for each cohort, they were harmonised following the LifeCycle protocol (López Vicente et al., 2019) based on prior studies that required the combination of data coming from different cohorts (Vilahur et al., 2014; Villanueva et al., 2018). This harmonization procedure began with the calculation of z-scores (subtracting the mean from the raw score and dividing by the standard deviation). In a second stage, these scores were multiplied by 15 and 100 points were added so they presented a standardised distribution with M = 100 and SD = 15.

2.2.4 Covariates

The set of covariates selected for this study were: sex of the child (female/male); age when the WM test was conducted; preterm birth (<37 weeks of pregnancy, yes/no); and birthweight (in grams). We used maternal educational attainment (primary, secondary, university) and the EUSILC index of total disposable family income (Pizzi et al., 2020) as indicators of socio-economic status. The EUSILC index was not available for ALSPAC so we used maternal occupational status instead, which corresponded to the International Standard Classification of Occupations 1988 (ISCO 1988; https://ec.europa.eu/eurostat/documents/1978984/6037342/ISCO-88-COM.pdf). All the covariates were harmonised following the procedure described elsewhere (Pinot De Moira et al., 2021).

2.4 Data analysis

The dataset was analysed using R software v.4.0.3 (R Core Team, 2022). After estimating descriptive statistics, we applied the principles of robust causal inference to select the covariates to be included in the statistical models. We started by adapting the Direct Acyclic Graph (DAG) from a previous study on greenness and WM (Subiza-Pérez et al., 2023; see Figure 1) and validating it separately for each cohort and follow-up, following the procedure described elsewhere (Ankan et al., 2021; Subiza-Pérez et al., 2024, 2023) and using R packages dagitty (Textor, 2020; Textor et al., 2017) and lavaan (Rosseel, 2012). In line with these previous studies, we considered testable implications as unmet when their associated p-values were lower than 0.05 and the r-scores larger than 0.20. The minimum adjustment sets of variables were identified via the dagitty function adjustmentSets(). This process was applied to the complete cases datasets (i.e., analytical samples hereafter)[1].

[1] There were substantial missing variables in the socio-economic and environmental variables in the two British cohorts. In order to see whether the analytical samples differed from the initial ones, we run a series of chi-square and Welch t-tests. However, the results of these analyses revealed that there were not statistically relevant differences between the two sets of samples (see Supplementary Tables 1 and 2).

We used the functions included in *stats* and *medflex* R packages to fit the linear regression models and extract the coefficients indicative of the total, direct and indirect (i.e., through air pollution), associations of greenness metrics with WM scores (Steen et al., 2017). We did this for each combination of exposure, outcome, cohort, and follow-up, resulting in 16 models. For those models with NDVI as the predictor variable, the coefficients reflect changes in WM scores by NDVI increases of 1 IQR (see specific sample IQRs in Supplementary Table 3). Given the nature of the set of exposure variables here considered these analyses were all cross-sectional.

Once we quantified the associations for each cohort experiment, we combined the available evidence from all cohorts using meta-analysis methodology (Higgins and Green, 2008). For this purpose, we used the function metagen() of the R package meta (Balduzzi et al., 2019), applying the generic inverse variance method for pooling the available data of the response variable (Borenstein et al., 2010).

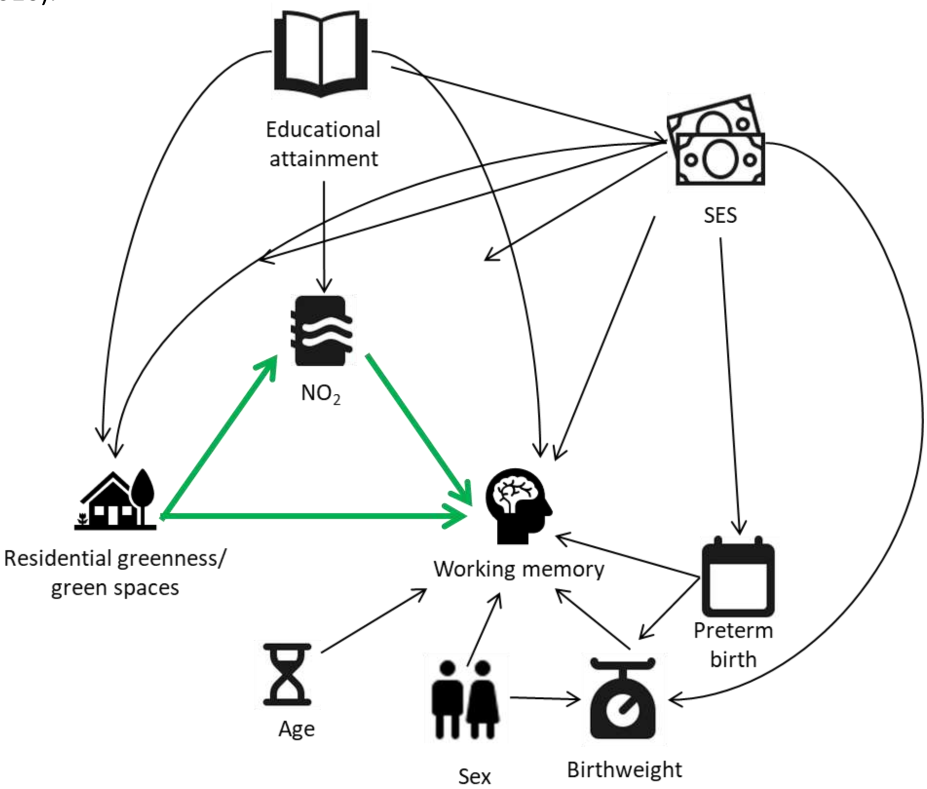

Figure 1. DAG explaining the relationship between exposure to residential green space and working memory. Arrows highlighted in green correspond to the effects of interest for this study. SES = EUSILC index of total disposable family income for BiB, INMA 6 to 8 and INMA 10 to 12 years samples. Maternal occupational status for ALSPAC. NO_2 = nitrogen dioxide.

3. Results

3.1 Sample description and DAG validation

The analytical samples comprised 6,760 participants distributed among the four study samples (see Table 1). These samples were evenly distributed in terms of sex, except for INMA 6 to 8 years follow-up sample in which a greater proportion of males was observed. Preterm birth was below the 5% of the samples and was slightly higher in the British samples. In terms of maternal educational attainment, we found relevant differences between the samples. Most ALSPAC mothers were moderately educated whereas those included in the BiB sample had low educational attainment. Mothers in INMA clustered among the medium and high levels of educational attainment. Regarding greenspace availability, most of the participants (>70%) lived within 300 m of a green space larger than 5,000 m^2, but that figure was higher for those participants in the Spanish samples. In contrast, the observed NDVI values were larger in ALSPAC and BiB than INMA. Concentrations of NO_2 were similar among the samples, although a greater between-participant variability was observed in the INMA samples.

None of the testable assumptions implied in the DAG obtained r-coefficients above 0.20 and p-values below 0.05 (see Appendix I) in the ALSPAC, BiB and INMA 10 to 12 years follow-up samples, so the initial DAG was considered correct for these samples. However, two testable implications were unmet in the case of the INMA 6 to 8 years follow-up; "greenness metric $\perp$ age" and "NO_2 $\perp$ age", which indicated that exposures were not independent of the age when the WM test was conducted. We updated the study DAG with these relationships (see Supplementary Figure 1) and extracted the minimum set of adjustment variables for the total association models, which was composed of maternal education and family income for all the models. In addition, age was included in the models involving the INMA 6 to 8 years follow up sample. For the direct association models, the adjustment set also included NO_2.

3.2 Separate models

Table 2 shows the results of the separate linear regression models. We found a consistent positive association between NDVI and WM scores in BiB and INMA 6 to 8 years cohorts; participants living in greener residential settings scored higher in the computerized WM task. In the case of BiB, we also observed that availability of green spaces was positively associated with the outcome. However, we could not confirm the mediation via NO_2 as all the indirect association coefficients but one fell above the p = 0.05 threshold. For the cohorts and follow-ups involving older participants (i.e., ALSPAC and INMA 10 to 12 years), none of the models revealed statistically significant associations, so neither residential greenness nor green space availability predicted WM scores. See the graphical depictions of these associations, along with the distribution of residuals in Supplementary figures 2A and 2B.

3.3 Meta-analysis

Figure 2 and Supplementary Figure 2 show the results of the meta-analysis. The only integrated estimate showing a statistically significant association was that of NDVI 100 m [0.48, (95%CI = 0.05 – 0.91)], indicating greater WM scores for those participants living in greener areas. The rest of the combined estimates, albeit suggestive of a positive association, did not reach statistical significance. Meta-analytic estimates revealed a high level of heterogeneity between the individual studies (I^2 = 45 – 76%). The forest (Figure 2) and the funnel (Supplementary Figure 3) plots confirmed what was found in the earlier stage of the analysis as they showed how the connection between residential greenness and green space availability was stronger and statistically significant only in BiB and the INMA 6 to 8 years follow up samples.

Table 1 Description of study variables in study samples. Numbers represent mean scores in continuous variables and frequencies in categorical ones. Scores within parentheses indicate the proportion of participants in the corresponding categories or the standard deviation in continuous variables.

Cohort	N	Sex	Age (in years)	Preterm birth	BW (in grams)	Ed. attainment	EUSILC	Green space avail.	NDVI100	NDVI300	NDVI500	NO_2 (in µg/ m^3)	WM
ALSPAC 10-12	1971	♂ 958 (48.60%) ♀ 1013 (51.40%)	10.61 (0.23)	83 (4.21%)	3450 (522.01)	High 396 (20.09%) Medium 1420 (72.04%) Low 155 (7.87%)	NA	Yes 1522 (77.22%) No 449 (22.88%)	0.39 (0.10)	0.48 (0.10)	0.49 (0.10)	22.21 (3.42)	101.30 (13.53)
BiB 7-10	2606	♂ 1268 (48.66%) ♀ 1338 (51.34%)	7.90 (0.74)	121 (4.64%)	3195.38 (527.28)	High 696 (26.71%) Medium 387 (14.85%) Low 1523 (58.44%)	6.88 (0.25)	Yes 1922 (73.75%) No 684 (26.25%)	0.41 (0.11)	0.43 (0.10)	0.45 (0.10)	17.32 (1.53)	100.45 (15.13)
INMA 6 to 8	1126	♂ 674 (59.86%) ♀ 452 (40.14%)	7.55 (0.55)	31 (2.75%)	3260.46 (448.02)	High 435 (38.63%) Medium 458 (40.67%) Low 233 (20.70%)	7.12 (0.31)	Yes 972 (86.32%) No 154 (86.32%)	0.25 (0.11)	0.29 (0.13)	0.33 (0.14)	25.5 (12.97)	100.15 (14.98)
INMA 10 to 12	1057	♂ 503 (47.59%) ♀ 554 (52.41%)	10.83 (0.56)	26 (2.46%)	3271.16 (448.33)	High 419 (39.64%) Medium 428 (40.49%) Low 210 (19.87%)	7.14 (0.31)	Yes 897 (84.86%) No 160 (15.14%)	0.27 (0.13)	0.32 (0.14)	0.35 (0.15)	22.23 (12.55)	99.66 (15.21)

Note: BW = Birth Weight, EUSILC = index of total disposable family income. NDVI 100, 300, and 500: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers. NO_2 = Nitrogen dioxide, WM = Working Memory. 'Green availability' refers to major greenspace (>5000 m²) within 300m of home address, including green urban areas, forests, and agricultural areas.

Table 2. Results of the linear regression models showing the total, direct and indirect associations between residential greenness metrics and working memory scores by cohort and follow-up.

Cohort	**Exposure**																				
		NDVI 100					**NDVI 300**					**NDVI 500**					**Green availability**				
	Association	**Coefficient**	**SE**	**95%CI**	***t***	***p*-value**	**Coefficient**	**SE**	**95%CI**	***t***	***p*-value**	**Coefficient**	**SE**	**95%CI**	***t***	***p*-value**	**Coefficient**	**SE**	**95%CI**	***t***	***p*-value**
INMA 6-8 years	Total	1.07	0.61	(-0.13, 2.26)	1.75	0.08	**1.64**	**0.72**	**(0.23, 3.05)**	**2.29**	**0.022**	**1.84**	**0.73**	**(0.40, 3.28)**	**2.51**	**0.012**	-0.64	1.35	(-3.28, 2)	-0.47	0.634
	Direct	1.06	0.69	(-0.30. 2.42)	1.52	0.128	**1.85**	**0.9**	**(0.08, 3.63)**	**2.05**	**0.041**	**2.36**	**-0.97**	**(0.47, 4.26)**	**2.45**	**0.015**	-1.22	1.47	(-4.10, 1.65)	-0.83	0.404
	Indirect	0.11	0.35	(-0.58, 0.80)	0.31	0.76	-0.26	0.48	(-1.22, 0.68)	-0.54	0.585	-0.51	0.58	(-1.67, 0.58)	-0.88	0.382	**1.47**	**0.71**	**(0.10, 2.88)**	**2.07**	**0.038**
BiB 7-10 years	Total	**1.66**	**0.45**	**(0.77, 2.53)**	**3.71**	**<.001**	**1.52**	**0.52**	**(0.50, 2.53)**	**2.95**	**0.003**	**1.42**	**0.49**	**(0.46, 2.38)**	**2.9**	**0.004**	**1.63**	**0.68**	**(0.30, 2.99)**	**2.39**	**0.017**
	Direct	**1.61**	**0.46**	**(-0.15, 0.26)**	**3.48**	**<.001**	**1.43**	**0.52**	**(0.41, 2.44)**	**2.75**	**0.006**	**1.35**	**0.49**	**(0.39, 2.33)**	**2.74**	**0.006**	**1.65**	**0.69**	**(0.32, 3)**	**2.4**	**0.016**
	Indirect	0.06	0.1	(-0.15, 0.26)	0.53	0.597	0.09	0.12	(-0.14, 0.32)	0.77	0.442	0.06	0.06	(-0.05, 0.18)	1.09	0.275	-0.01	0.02	(-0.06, 0.03)	-0.6	0.549
ALSPAC 10-12 years	Total	-0.04	0.31	(-0.64, 0.56)	-0.13	0.896	-0.2	0.31	(-0.82, 0.39)	-0.64	0.52	-0.3	0.44	(-1.18, 0.55)	-0.68	0.498	-0.31	0.7	(-1.71, 1.05)	-0.44	0.66
	Direct	0.14	0.33	(-0.50, 0.78)	0.43	0.666	0.16	0.4	(-0.63, 0.92)	0.4	0.692	0.24	0.56	(-0.91, 1.36)	0.41	0.683	-0.01	0.73	(-1.48, 1.38)	-0.02	0.985
	Indirect	-0.18	0.11	(-0.40, 0.04)	-1.61	0.107	-0.36	0.25	(-0.84, 0.13)	-1.44	0.149	-0.53	0.37	(-1.26, 0.18)	-1.45	0.147	-0.3	0.2	(-0.67, 0.11)	-1.49	0.136
INMA 10-12 years	Total	-0.24	0.6	(-1.41, 0.94)	-0.39	0.694	-0.36	0.68	(-1.69, 0.97)	-0.53	0.596	-0.57	0.74	(-2.01, 0.88)	-0.77	0.443	-0.53	1.29	(-3.07, 2)	-0.41	0.679
	Direct	0.41	0.76	(-1.07, 1.90)	0.55	0.584	0.52	0.95	(-1.35, 2.40)	0.55	0.583	0.35	1.1	(-1.82, 2.52)	0.32	0.751	0.27	1.49	(-2.64, 3.19)	0.18	0.853
	Indirect	-0.64	0.45	(-1.54, 0.24)	-1.4	0.160	-0.87	0.71	(-2.25, 0.53)	-1.24	0.216	-0.89	0.87	(-2.58, 0.83)	-1.03	0.305	-0.85	0.73	(-2.30, 0.56)	-1.17	0.243

Note: NDVI 100, 300, and 500: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers. 'Green availability' refers to major greenspace (>5000 m²) within 300m of home address, including green urban areas, forests, and agricultural areas. Covariates: maternal educational attainment and family socioeconomic status. Models fitted with data from INMA 6-8 years follow-up were additionally adjusted for age due to the amendments made to the DAG after its validation.

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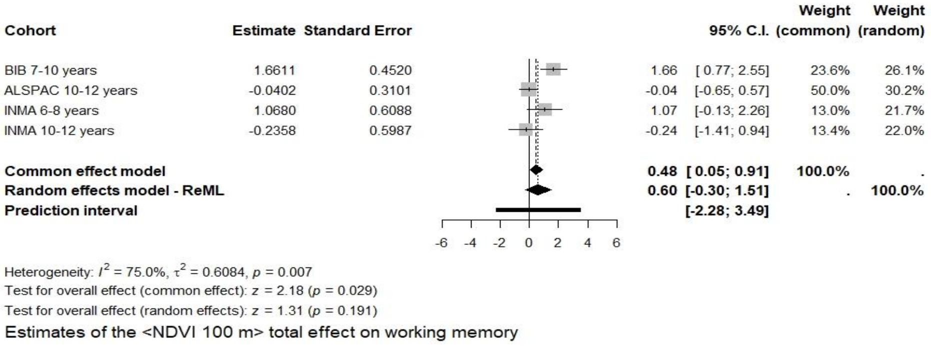

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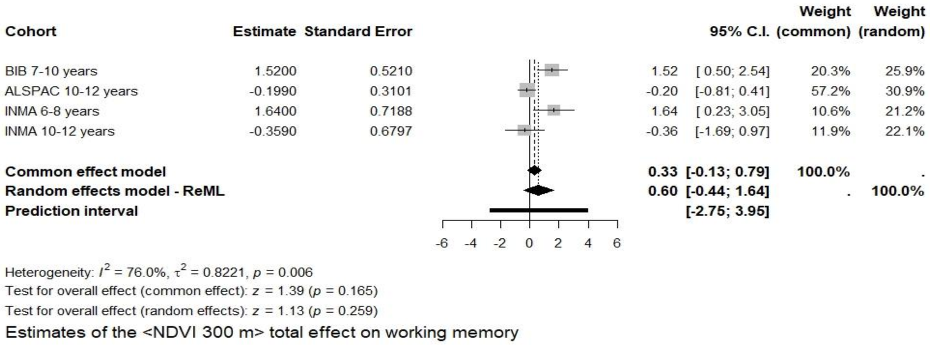

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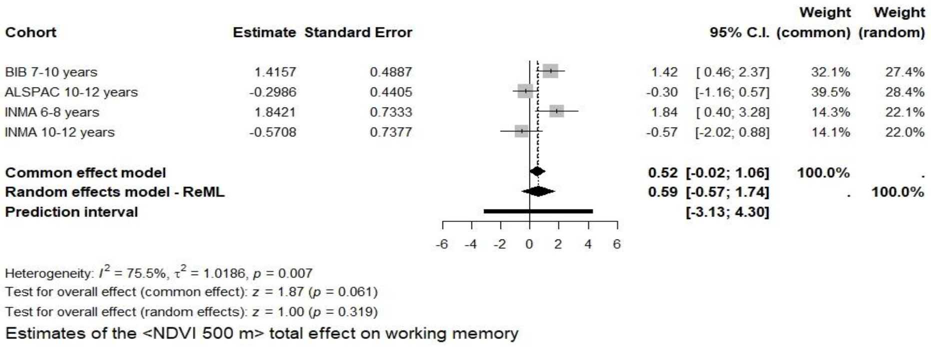

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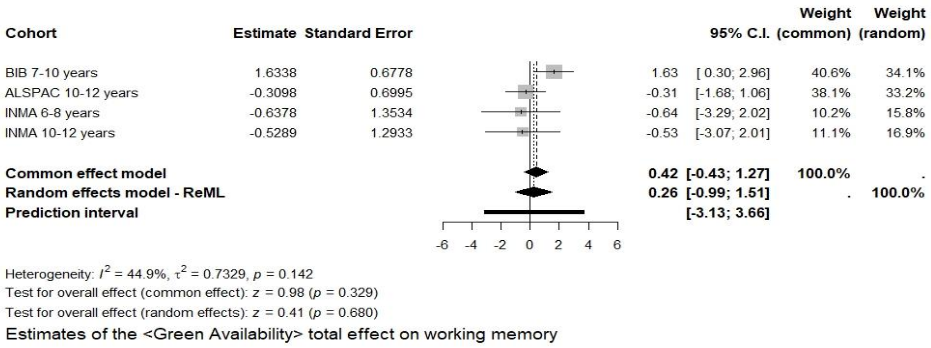

Figure 2. Results of the meta-analysis combining the estimates of the individual cohort models. NDVI 100 m (first), NDVI 300 m (second), NDVI 500 m (third) and green space availability (fourth).

4. Discussion

We aimed to produce new scientific evidence that could contribute towards a consensus on the associations between residential greenness and WM during childhood and pre-adolescence. This is needed because the current epidemiological evidence is mixed. The systematic review by Buczyłowska and colleagues (2023) indicated that only four out of seven of the published observational studies in the field were able to statistically confirm the hypothesised protective greenness-WM links during childhood and adolescence. Similarly, a systematic review and meta-analysis published after the conduction of the analysis presented in this piece, and therefore not described in the introduction of this paper, synthesized the results of 22 correlational studies using residential greenness metrics and found no overall association between those and cognitive performance in children and adolescents (Nguyen and Walters, 2024). In line with this picture, our results are far from consistent. We found that residential greenness, in the form of NDVI, was positively associated with WM scores but only for those participants between 6 and 10 years of age. However, the resulting coefficient showed a high degree of heterogeneity, which limits its generalizability. For older groups, NDVI values did not predict WM scores. Moreover, the availability of green spaces near the household showed a beneficial association with WM memory in BiB but that could not be confirmed in the other cohorts. Finally, and contrary to theoretical expectations (Markevych et al., 2017) and previous studies (Dadvand et al., 2015), we did not find support for the air pollution reduction pathway.

A potential explanation for our results could be the existence of a window of exposure by which children and adolescents are more susceptible to the potential benefits of greenness and green spaces in certain moments of their development (i.e., before and the 10 to 13 years period of latency described by Ahmed et al., 2022 and Reynolds et al., 2022). Another potentially compatible explanation relates to the observed changes in the use of greenspaces that occur from childhood to adolescence (Marquet et al., 2019). In the Marquet et al study, which analysed data from *in situ* observations in parks in the city of New York, the authors reported that use decreased with age as younger children were observed more often in the parks than teenagers.

In order to test this possibility, we reviewed the studies compiled by Buczyłowska and colleagues (2023) and the one by Fernandes et al. (2023) to see whether the pattern of statistically significant vs non-significant results aligned with the childhood-adolescence gap suggested here. The age of participants in the studies that reported significant beneficial associations greenness and/or green spaces are as follows: 4 to 6 years (Dockx et al., 2022), 7 to 13 years (Dadvand et al., 2015), 9 to 15 years (Maes et al., 2021) and 11 years (Flouri et al., 2019). On the other hand, those not reporting statistically significant results analysed data from samples composed of participants 5 to 18 years (Reuben et al., 2019), 6 to 11 years (Fernandes et al., 2023; Julvez et al., 2021) and 13 to 17 years (Bijnens et al., 2022). The picture that emerges from this revision, also supported with the results of our work, is that the statistically significant and non-significant results do not cluster by age and therefore more studies are needed to establish a scientific consensus.

4.1 Study strengths and limitations

This study contributes to the specific literature on residential greenness and WM for a number of reasons. First, it makes available the estimates of the association between residential greenness and availability of green spaces with WM scores in an overall sample of 6,818 children and adolescents. This sample size is relevant given that previous evidence is based on a total of 16,508 participants

(Buczyłowska et al., 2023; Fernandes et al., 2023). Second, we used a DAG and the d-separation criterion to select the set of adjustment variables DAG (Ankan et al., 2021 ; Elwert, 2013; Pearl, 2000; Tennant et al., 2021; Textor et al., 2017). Also in the methodological sphere, we meta-analysed the coefficients estimated for each cohort study which allowed us to interpret results beyond previous narrative assessments (Buczyłowska et al., 2023). Finally, despite of the fact that two previous works utilised part of the available residential greenness and WM data within the A EU Child Cohort Network consortium (Fernandes et al., 2023; Subiza-Pérez et al., 2023), this is the first comprehensive study using all available data.

However, there are some limitations that need to be acknowledged when interpreting our results and that are pervasive in this area of research. We focused on the home environment and therefore neglected other relevant environments that may have an impact on behaviour and development, such as the school or leisure areas. This has been referred to as the *uncertain geographic context problem* (Kwan, 2012, 2009). Moreover, and in line with Labib and colleagues (2020), our study does not account for the frequency and duration of residential green space use, if any, and their quality, design and safety features. In terms of the outcome, the measurement of WM was not fully consistent across cohorts. We encourage future researchers in this are to employ a consensual strategy that could lead to more homogenous evidence. Furthermore, given that we studied the cross-sectional associations between greenness metrics and WM scores we cannot make inferences about potential long-term effects (e.g., early childhood exposure). Despite the fact that we could not control for it due to the nature of our greenness metrics (i.e., NDVI values corresponding to the period of maximum vegetation), one of the anonymous reviewers insightfully pointed out that the potential confounding effects of seasonality, given the season variations observed in both greenness (Klimavičius et al., 2023; Naif et al., 2020) and cognitive performance (Hohm et al., 2024; Meyer et al., 2016) metrics. We consider that future research on greenness and executive functions should consider this aspect. We did not explore pathways other than the reduction of NO_2 concentrations, and therefore we lack specific information about other pollutants (e.g., particulate matter) and other potential pathways such as the promotion of physical activity or social cohesion (Markevych et al., 2017). Nevertheless, from a formal point of view, the potential association through those other pathways are included within the direct association estimates. We used a complete case analysis approach, since there were no statistically significant differences between the missingness of covariates and the exposure or the outcome (Missing at Random-MAR hypothesis). Our choice led to unbiased estimates, although it resulted in a potential loss of statistical power. In this context, it also needs to be acknowledged that, given that our participants enrolled in the cohort study and the subsequent follow-ups voluntarily, our study might be affected by selection bias. Despite some previous works using part of the available residential greenness and WM data within the A EU Child Cohort Network consortium study (Fernandes et al., 2023; Subiza-Pérez et al., 2023), this study is the first one using all the data available in the consortium. Both the analysis of the BiB and ALSPAC datasets, and the meta-analytic approach is original to the study presented here.

5. Final remarks

This study aimed to provide further evidence on the potential benefits of residential greenness and green spaces on WM during childhood and adolescence. We found some support for a beneficial association in children between 6 and 10 years of age which could not be confirmed for older participants. More studies and meta-analysis are needed to achieve a scientific consensus.

Ahmed, S.F., Ellis, A., Ward, K.P., Chaku, N., Davis-kean, P.E., Ahmed, S.F., Ellis, A., Ward, K.P., Chaku, N., Davis-kean, P.E., 2022. Developmental Psychology Two Nationally Representative Samples Working Memory Development From Early Childhood to Adolescence Using Two Nationally Representative Samples. Developmental Psychology 1–11.

Alemany, S., Vilor-Tejedor, N., García-Esteban, R., Bustamante, M., Dadvand, P., Esnaola, M., Mortamais, M., Forns, J., van Drooge, B.L., Álvarez-Pedrerol, M., Grimalt, J.O., Rivas, I., Querol, X., Pujol, J., Sunyer, J., 2018. Traffic-related air pollution, APOE ∊4 status, and neurodevelopmental outcomes among school children enrolled in the BREATHE project (Catalonia, spain). Environmental Health Perspectives 126, 1–11. https://doi.org/10.1289/EHP2246

Ankan, A., Wortel, I.M.N., Textor, J., 2021. Testing Graphical Causal Models Using the R Package “dagitty.” Current Protocols 1, 1–22. https://doi.org/10.1002/cpz1.45

Baddeley, A., 1992. Working Memory. Science 255, 556–559.

Balduzzi, S., Rücker, G., Schwarzer, G., 2019. How to perform a meta-analysis with R: a practical tutorial. Evid Based Mental Health 22, 153–160. https://doi.org/10.1136/ebmental-2019-300117

Beelen, R., Hoek, G., Vienneau, D., Eeftens, M., Dimakopoulou, K., Pedeli, X., Tsai, M.Y., Künzli, N., Schikowski, T., Marcon, A., Eriksen, K.T., Raaschou-Nielsen, O., Stephanou, E., Patelarou, E., Lanki, T., Yli-Tuomi, T., Declercq, C., Falq, G., Stempfelet, M., Birk, M., Cyrys, J., von Klot, S., Nádor, G., Varró, M.J., Dedele, A., Gražulevičiene, R., Mölter, A., Lindley, S., Madsen, C., Cesaroni, G., Ranzi, A., Badaloni, C., Hoffmann, B., Nonnemacher, M., Krämer, U., Kuhlbusch, T., Cirach, M., de Nazelle, A., Nieuwenhuijsen, M.J., Bellander, T., Korek, M., Olsson, D., Strömgren, M., Dons, E., Jerrett, M., Fischer, P.H., Wang, M., Brunekreef, B., de Hoogh, K., 2013. Development of NO2 and NOx land use regression models for estimating air pollution exposure in 36 study areas in Europe - The ESCAPE project. Atmospheric Environment 72, 10–23. https://doi.org/10.1016/j.atmosenv.2013.02.037

Bijnens, E.M., Vos, S., Verheyen, V.V., Bruckers, L., Covaci, A., De Henauw, S., Den Hond, E., Loots, I., Nelen, V., Plusquin, M., Schoeters, G., Nawrot, T.S., 2022. Higher surrounding green space is associated with better attention in Flemish adolescents. Environment International 159, 107016. https://doi.org/10.1016/j.envint.2021.107016

Binter, A., Bernard, J.Y., Mon-williams, M., Andiarena, A., González-Safont, L., Vafeiadi, M., Lepeule, J., Soler-Blasco, R., Kampouri, M., Alonso, L., Mceachan, R., Santa-Marina, L., Wright, J., Chatzi, L., Sunyer, J., Philippat, C., Nieuwenhuijsen, M., Vrijheid, Ma., Guxens, M., 2022. Urban environment and cognitive and motor function in children from four European birth cohorts. Environment International journal 158. https://doi.org/10.1016/j.envint.2021.106933

Borenstein, M., Hedges, L.V., Higgins, J., Rothstein, H.R., 2010. A basic introduction to fixed-effect and random-effects models for meta-analysis. Research Synthesis Methods# 97–111. https://doi.org/10.1002/jrsm.12

Boyd, A., Golding, J., Macleod, J., Lawlor, D.A., Fraser, A., Henderson, J., Molloy, L., Ness, A., Ring, S., Davey Smith, G., 2013. Cohort Profile: The ‘Children of the 90s’—the index offspring of the Avon Longitudinal Study of Parents and Children. International Journal of Epidemiology 42, 111–127. https://doi.org/10.1093/ije/dys064

Buczyłowska, D., Zhao, T., Singh, N., Jurczak, A., Siry, A., Markevych, I., 2023. Exposure to greenspace and bluespace and cognitive functioning in children – A systematic review. Environmental Research 222. https://doi.org/10.1016/j.envres.2023.115340

Copernicus, 2012. Urban Atlas.

Copernicus, 2006. Urban Atlas.

Cowan, N., 2014. Working Memory Underpins Cognitive Development, Learning, and Education. Educational Psychology Review 26, 197–223. https://doi.org/10.1007/s10648-013-9246-y

Dadvand, P., Nieuwenhuijsen, M.J., Esnaola, M., Forns, J., Basagaña, X., Alvarez-Pedrerol, M., Rivas, I., López-Vicente, M., De Pascual, M.C., Su, J., Jerrett, M., Querol, X., Sunyer, J., 2015. Green spaces and cognitive development in primary schoolchildren. Proceedings of the National Academy of Sciences of the United States of America 112, 7937–7942. https://doi.org/10.1073/pnas.1503402112

De Hoogh, K., Chen, J., Gulliver, J., Hoffmann, B., Hertel, O., Ketzel, M., Bauwelinck, M., Van Donkelaar, A., Hvidtfeldt, U.A., Katsouyanni, K., Klompmaker, J., Martin, R.V., Samoli, E., Schwartz, P.E., Stafoggia, M., Bellander, T., Strak, M., Wolf, K., Vienneau, D., Brunekreef, B., Hoek, G., 2018. Spatial PM2.5, NO2, O3 and BC models for Western Europe – Evaluation of spatiotemporal stability. Environment International 120, 81–92. https://doi.org/10.1016/j.envint.2018.07.036

Dockx, Y., Bijnens, E.M., Luyten, L., Peusens, M., Provost, E., Rasking, L., Sleurs, H., Hogervorst, J., Plusquin, M., Casas, L., Nawrot, T.S., 2022. Early life exposure to residential green space impacts cognitive functioning in children aged 4 to 6 years. Environment International 161, 107094. https://doi.org/10.1016/j.envint.2022.107094

Dzhambov, A.M., Browning, M.H.E.M., Markevych, I., Hartig, T., Lercher, P., 2020. Analytical approaches to testing pathways linking greenspace to health: A scoping review of the empirical literature. Environmental Research 186, 109613. https://doi.org/10.1017/CBO9781107415324.004

Estarlich, M., Ballester, F., Aguilera, I., Fernández-Somoano, A., Lertxundi, A., Llop, S., Freire, C., Tardón, A., Basterrechea, M., Sunyer, J., Iñiguez, C., 2011. Residential Exposure to Outdoor Air Pollution during Pregnancy and Anthropometric Measures at Birth in a Multicenter Cohort in Spain. Environ Health Perspect 119, 1333–1338. https://doi.org/10.1289/ehp.1002918

Fernandes, A., Krog, N.H., McEachan, R., Nieuwenhuijsen, M., Julvez, J., Márquez, S., De Castro, M., Urquiza, J., Heude, B., Vafeiadi, M., Gražulevičienė, R., Slama, R., Dedele, A., Aasvang, G.M., Evandt, J., Andrusaityte, S., Kampouri, M., Vrijheid, M., 2023. Availability, accessibility, and use of green spaces and cognitive development in primary school children. Environmental Pollution 334, 122143. https://doi.org/10.1016/j.envpol.2023.122143

Flouri, E., Papachristou, E., Midouhas, E., 2019. The role of neighbourhood greenspace in children's spatial working memory. British Journal of Educational Psychology 89, 359–373. https://doi.org/10.1111/bjep.12243

Forns, J., Dadvand, P., Esnaola, M., Alvarez-Pedrerol, M., López-Vicente, M., Garcia-Esteban, R., Cirach, M., Basagaña, X., Guxens, M., Sunyer, J., 2017. Longitudinal association between air pollution exposure at school and cognitive development in school children over a period of 3.5 years. Environmental Research 159, 416–421. https://doi.org/10.1016/j.envres.2017.08.031

Fossati, S., Nieuwenhuijsen, M., Vrijheid, M., 2019. Protocol for integrated urban environment stressors 1–52.

Fraser, A., Macdonald-Wallis, C., Tilling, K., Boyd, A., Golding, J., Davey Smith, G., Henderson, J., Macleod, J., Molloy, L., Ness, A., Ring, S., Nelson, S.M., Lawlor, D.A., 2013. Cohort Profile: The Avon Longitudinal Study of Parents and Children: ALSPAC mothers cohort. International Journal of Epidemiology 42, 97–110. https://doi.org/10.1093/ije/dys066

Guxens, M., Ballester, F., Espada, M., Fernández, M.F., Grimalt, J.O., Ibarluzea, J., Olea, N., Rebagliato, M., Tardón, A., Torrent, M., Vioque, J., Vrijheid, M., Sunyer, J., 2012. Cohort profile: The INMA-INfancia y Medio Ambiente-(environment and childhood) project. International Journal of Epidemiology 41, 930–940. https://doi.org/10.1093/ije/dyr054

Higgins, J., Green, S., 2008. Cochrane Handbook for Systematic Reviews of Interventions. The Cochrane Collaboration.

Hill, L.J., Shire, K.A., Allen, R.J., Crossley, K., Wood, M.L., Mason, D., Waterman, A.H., 2022. Large-scale assessment of 7-11-year-olds' cognitive and sensorimotor function within the Born in Bradford longitudinal birth cohort study. Wellcome Open Research 6. https://doi.org/10.12688/wellcomeopenres.16429.2

Hohm, I., Wormley, A.S., Schaller, M., Varnum, M.E.W., 2024. Homo temporus: Seasonal Cycles as a Fundamental Source of Variation in Human Psychology. Perspectives on Psychological Science 19, 151–172.

Julvez, J., López-Vicente, M., Warembourg, C., Maitre, L., Philippat, C., Gützkow, K.B., Guxens, M., Evandt, J., Andrusaityte, S., Burgaleta, M., Casas, M., Chatzi, L., de Castro, M., Donaire-González, D., Gražulevičienė, R., Hernandez-Ferrer, C., Heude, B., Mceachan, R., Mon-Williams, M., Nieuwenhuijsen, M., Robinson, O., Sakhi, A.K., Sebastian-Galles, N., Slama, R., Sunyer, J., Tamayo-Uria, I., Thomsen, C., Urquiza, J., Vafeiadi, M., Wright, J., Basagaña, X., Vrijheid, M., 2021. Early Life Multiple Exposures and Child Cognitive Function: A Multi-Centric Birth Cohort Study in Six European Countries. Environmental Pollution 284, 117404. https://doi.org/10.1016/j.envpol.2021.117404

Klimavičius, L., Rimkus, E., Stonevičius, E., Mačiulytė, V., 2023. Seasonality and long-term trends of NDVI values in different land use types in the eastern part of the Baltic Sea basin. Oceanologia 65, 171–181. https://doi.org/10.1016/j.oceano.2022.02.007

Klingberg, J., Broberg, M., Strandberg, B., Thorsson, P., Pleijel, H., 2017. Influence of urban vegetation on air pollution and noise exposure – A case study in Gothenburg, Sweden. Science of the Total Environment 599–600, 1728–1739. https://doi.org/10.1016/j.scitotenv.2017.05.051

Kwan, M.P., 2012. The Uncertain Geographic Context Problem. Annals of the Association of American Geographers 102, 958–968. https://doi.org/10.1080/00045608.2012.687349

Kwan, M.P., 2009. From place-based to people-based exposure measures. Social Science and Medicine 69, 1311–1313. https://doi.org/10.1016/j.socscimed.2009.07.013

Labib, S.M., Lindley, S., Huck, J.J., 2020. Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review. Environmental Research 180, 108869. https://doi.org/10.1016/j.envres.2019.108869

Lindén, J., Gustafsson, M., Uddling, J., Watne, Å., Pleijel, H., 2023. Air pollution removal through deposition on urban vegetation: The importance of vegetation characteristics. Urban Forestry & Urban Greening 81, 127843. https://doi.org/10.1016/j.ufug.2023.127843

López Vicente, M., Julvez, J., Garcia, R., Fernandez, S., Sunyer, J., 2019. Harmonization Manual WP6: Mental Health.

Maes, M.J.A., Pirani, M., Booth, E.R., Shen, C., Milligan, B., Jones, K.E., Toledano, M.B., 2021. Benefit of woodland and other natural environments for adolescents' cognition and mental health. Nat Sustain 4, 851–858. https://doi.org/10.1038/s41893-021-00751-1

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., de Vries, S., Triguero-Mas, M., Brauer, M., Nieuwenhuijsen, M.J., Lupp, G., Richardson, E.A., Astell-Burt, T., Dimitrova, D., Feng, X., Sadeh, M., Standl, M., Heinrich, J., Fuertes, E., 2017. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. Environmental Research 158, 301–317. https://doi.org/10.1016/j.envres.2017.06.028

Marquet, O., Hipp, J.A., Alberico, C., Huang, J.-H., Mazak, E., Fry, D., Lovasi, G.S., Floyd, M.F., 2019. How Does Park Use and Physical Activity Differ between Childhood and Adolescence? A Focus on Gender and Race-Ethnicity. J Urban Health 96, 692–702. https://doi.org/10.1007/s11524-019-00388-8

McEachan, R.R.C., Santorelli, G., Watmuff, A., Mason, D., Barber, S.E., Bingham, D.D., Bird, P.K., Lennon, L., Lewer, D., Mon-Williams, M., Shire, K.A., Waiblinger, D., West, J., Yang, T.C., Lawlor, D.A., Pickett, K.E., Wright, J., 2024. Cohort Profile Update: Born in Bradford. International Journal of Epidemiology 53, dyae037. https://doi.org/10.1093/ije/dyae037

Meyer, C., Muto, V., Jaspar, M., Kussé, C., Lambot, E., Chellappa, S.L., Degueldre, C., Balteau, E., Luxen, A., Middleton, B., Archer, S.N., Collette, F., Dijk, D.-J., Phillips, C., Maquet, P., Vandewalle, G., 2016. Seasonality in human cognitive brain responses. Proc. Natl. Acad. Sci. U.S.A. 113, 3066–3071. https://doi.org/10.1073/pnas.1518129113

Nader, J.L., López-Vicente, M., Julvez, J., Guxens, M., Cadman, T., Elhakeem, A., Järvelin, M.-R., Rautio, N., Miettunen, J., El Marroun, H., Melchior, M., Heude, B., Charles, M.-A., Yang, T.C.,

McEachan, R.R.C., Wright, J., Polanska, K., Carson, J., Lin, A., Rauschert, S., Huang, R.-C., Popovic, M., Richiardi, L., Corpeleijn, E., Cardol, M., Mikkola, T.M., Eriksson, J.G., Salika, T., Inskip, H., Vinther, J.L., Strandberg-Larsen, K., Gürlich, K., Grote, V., Koletzko, B., Vafeiadi, M., Sunyer, J., Jaddoe, V.W.V., Harris, J.R., 2023. Measures of Early-life Behavior and Later Psychopathology in the LifeCycle Project - EU Child Cohort Network: A Cohort Description. Journal of Epidemiology 33, 321–331. https://doi.org/10.2188/jea.JE20210241
Naif, S.S., Mahmood, D.A., Al-Jiboori, M.H., 2020. Seasonal normalized difference vegetation index responses to air temperature and precipitation in Baghdad. Open Agriculture 5, 631–637. https://doi.org/10.1515/opag-2020-0065
Nguyen, L., Walters, J., 2024. Benefits of nature exposure on cognitive functioning in children and adolescents: A systematic review and meta-analysis. Journal of Environmental Psychology 96, 102336. https://doi.org/10.1016/j.jenvp.2024.102336
Nieuwenhuijsen, M.J., Agier, L., Basagaña, X., Urquiza, J., Tamayo-Uria, I., Giorgis-Allemand, L., Robinson, O., Siroux, V., Maitre, L., Castro, M. de, Valentin, A., Donaire, D., Dadvand, P., Aasvang, G.Marit., Krog, N.H., Schwarze, P.E., Chatzi, L., Grazuleviciene, R., Andrusaityte, S., Dedele, A., McEachan, R., Wright, J., West, J., Ibarluzea, J., Ballester, F., Vrijheid, M., Slama, R., 2019. Influence of the Urban Exposome on Birth Weight. EHP (in press) 127.
Nordbø, E.C.A., Nordh, H., Raanaas, R.K., Aamodt, G., 2018. GIS-derived measures of the built environment determinants of mental health and activity participation in childhood and adolescence: A systematic review. Landscape and Urban Planning 177, 19–37. https://doi.org/10.1016/j.landurbplan.2018.04.009
Peters, R.L., Sutherland, D., Dharmage, S.C., Lowe, A.J., Perrett, K.P., Tang, M.L.K., Lycett, K., Knibbs, L.D., Koplin, J.J., Mavoa, S., 2022. The association between environmental greenness and the risk of food allergy: A population-based study in Melbourne, Australia. Pediatric Allergy and Immunology 33, 1–12. https://doi.org/10.1111/pai.13749
Pinot De Moira, A., Haakma, S., Strandberg-Larsen, K., Van Enckevort, E., Kooijman, M., Cadman, T., Cardol, M., Corpeleijn, E., Crozier, S., Duijts, L., Elhakeem, A., Eriksson, J.G., Felix, J.F., Fernández-Barrés, S., Foong, R.E., Forhan, A., Grote, V., Guerlich, K., Heude, B., Huang, R.-C., Järvelin, M.-R., Jørgensen, A.C., Mikkola, T.M., Nader, J.L.T., Pedersen, M., Popovic, M., Rautio, N., Richiardi, L., Ronkainen, J., Roumeliotaki, T., Salika, T., Sebert, S., Vinther, J.L., Voerman, E., Vrijheid, M., Wright, J., Yang, T.C., Zariouh, F., Charles, M.-A., Inskip, H., Jaddoe, V.W.V., Swertz, M.A., Nybo Andersen, A.-M., 2021. The EU Child Cohort Network's core data: establishing a set of findable, accessible, interoperable and re-usable (FAIR) variables. Eur J Epidemiol 36, 565–580. https://doi.org/10.1007/s10654-021-00733-9
Pizzi, C., Richiardi, M., Charles, M.-A., Heude, B., Lanoe, J.-L., Lioret, S., Brescianini, S., Toccaceli, V., Vrijheid, M., Merletti, F., Zugna, D., Richiardi, L., 2020. Measuring Child Socio-Economic Position in Birth Cohort Research: The Development of a Novel Standardized Household Income Indicator. IJERPH 17, 1700. https://doi.org/10.3390/ijerph17051700
Reuben, A., Arseneault, L., Belsky, D.W., Caspi, A., Fisher, H.L., Houts, R.M., Moffitt, T.E., Odgers, C., 2019. Residential neighborhood greenery and children's cognitive development. Social Science and Medicine 230, 271–279. https://doi.org/10.1016/j.socscimed.2019.04.029
Reynolds, M.R., Niileksela, C.R., Gignac, G.E., Sevillano, C.N., 2022. Working Memory Capacity Development Through Childhood: A Longitudinal Analysis. Developmental Psychology 58, 1254–1263. https://doi.org/10.1037/dev0001360
Rosseel, Y., 2012. lavaan: An R Package for Structural Equation Modeling. Journal of Statistical Software 48, 1–36.
Shelton, J.T., Elliott, E.M., Matthews, R.A., Hill, B.D., Gouvier, W.D., 2010. The Relationships of Working Memory, Secondary Memory, and General Fluid Intelligence: Working Memory Is Special. Journal of Experimental Psychology: Learning Memory and Cognition 36, 813–820. https://doi.org/10.1037/a0019046

Steen, J., Loeys, T., Moerkerke, B., Vansteelandt, S., 2017. Medflex: An R package for flexible mediation analysis using natural effect models. Journal of Statistical Software 76. https://doi.org/10.18637/jss.v076.i11

Subiza-Pérez, M., García-Baquero, G., Fernández-Somoano, A., Guxens, M., González, L., Tardón, A., Dadvand, P., Estarlich, M., De Castro, M., McEachan, R.R.C., Ibarluzea, J., Lertxundi, N., 2023. Residential green and blue spaces and working memory in children aged 6–12 years old. Results from the INMA cohort. Health & Place 84, 103136. https://doi.org/10.1016/j.healthplace.2023.103136

Subiza-Pérez, M., Krenz, K., Watmuff, A., Yang, T., Gilbody, S., Vaughan, L., Wright, J., McEachan, R.R.C., 2024. Social inequalities, residential greenness and common mental disorders in women: evidence from the Born in Bradford family cohort study. Urban Forestry & Urban Greening 94, 128241. https://doi.org/10.1016/j.ufug.2024.128241

Sunyer, J., Esnaola, M., Alvarez-Pedrerol, M., Forns, J., Rivas, I., López-Vicente, M., Suades-González, E., Foraster, M., Garcia-Esteban, R., Basagaña, X., Viana, M., Cirach, M., Moreno, T., Alastuey, A., Sebastian-Galles, N., Nieuwenhuijsen, M., Querol, X., 2015. Association between Traffic-Related Air Pollution in Schools and Cognitive Development in Primary School Children: A Prospective Cohort Study. PLoS Medicine 12, 1–24. https://doi.org/10.1371/journal.pmed.1001792

Textor, J., 2020. Dagitty Manual.

Textor, J., van der Zander, B., Gilthorpe, M.S., Liśkiewicz, M., Ellison, G.T., 2017. Robust causal inference using directed acyclic graphs: The R package "dagitty." International Journal of Epidemiology 45, 1887–1894. https://doi.org/10.1093/ije/dyw341

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8, 127–149.

Vilahur, N., Fernández, M.F., Bustamante, M., Ramos, R., Forns, J., Ballester, F., Murcia, M., Riaño, I., Ibarluzea, J., Olea, N., Sunyer, J., 2014. In utero exposure to mixtures of xenoestrogens and child neuropsychological development. Environmental Research 134, 98–104. https://doi.org/10.1016/j.envres.2014.07.002

Villanueva, C.M., Gracia-Lavedan, E., Julvez, J., Santa-Marina, L., Lertxundi, N., Ibarluzea, J., Llop, S., Ballester, F., Fernández-Somoano, A., Tardón, A., Vrijheid, M., Guxens, M., Sunyer, J., 2018. Drinking water disinfection by-products during pregnancy and child neuropsychological development in the INMA Spanish cohort study. Environment International 110, 113–122. https://doi.org/10.1016/j.envint.2017.10.017

Vuontela, V., Steenari, M.R., Carlson, S., Koivisto, J., Fjällberg, M., Aronen, E.T., 2003. Audiospatial and visuospatial working memory in 6-13 year old school children. Learning and Memory 10, 74–81. https://doi.org/10.1101/lm.53503

WHO Regional Office for Europe, 2016. Urban green spaces and health 92.

Wright, J., Small, N., Raynor, P., Tuffnell, D., Bhopal, R., Cameron, N., Fairley, L., A Lawlor, D., Parslow, R., Petherick, E.S., Pickett, K.E., Waiblinger, D., West, J., 2013. Cohort profile: The born in bradford multi-ethnic family cohort study. International Journal of Epidemiology 42, 978–991. https://doi.org/10.1093/ije/dys112

Zhang, Y., Mavoa, S., Zhao, J., Raphael, D., Smith, M., 2020. The association between green space and adolescents mental well-being: A systematic review. International Journal of Environmental Research and Public Health 17, 1–26. https://doi.org/10.3390/ijerph17186640