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

AUTHOR ACCEPTED MANUSCRIPT

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1 1. *Introduction*

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

10 Environmental epidemiologists and researchers in related disciplines have been working
11 intensively during the past decade to map and quantify the potential salutogenic effects of green
12 spaces and greenness on a wide range of health outcomes (Dzhambov et al., 2020; Markevych et al.,
13 2017). One of the potential pathways for positive impact is the reduction of exposure to air pollutants
14 because: (i) pollutants may become deposited on vegetated surfaces (Lindén et al., 2023); (ii) green
15 spaces create an increased distance to emission sources such as roads (Klingberg et al., 2017). In this
16 context, the study of whether higher exposure to residential green spaces and greenness leads to
17 higher working memory scores has received considerable attention. A recently published systematic
18 review (Buczyłowska et al., 2023) compiled the results of seven observational studies linking green
19 space and greenness metrics with WM outcomes in participants of various ages between 4 and 18
20 years. Four of these studies showed statistically significant protective effects. The remaining three
21 studies did not find any supporting evidence. In a more recent study, not included in the systematic
22 review, marginally significant associations ($p < 0.10$) were found between both green space availability
23 and residential Normalized Difference Vegetation Index (NDVI) and WM scores and in a sample of over
24 1,600 children aged 6 to 11 years living in various European cities (Fernandes et al., 2023).

25 In the present study, we wanted to contribute to the debate by analysing new data that could
26 help clarify the associations, if any, between residential green spaces, greenness metrics and WM. In
27 addition, we wished to explore the specific issue of WM and reduced exposure to NO₂, a pollutant that
28 has been specifically linked to WM performance in childhood (Alemany et al., 2018; Fornes et al., 2017;
29 Sunyer et al., 2015).

30 2. *Methods*

31 2.1 *Sample of participants*

32 Data from participants in pregnancy cohorts included in the LifeCycle Project (Nader et al., 2023) was
33 accessed. More specifically, we included data from those cohorts with available residential greenness
34 metrics and WM data during childhood. From 19 participating cohorts, we requested data to Avon
35 Longitudinal Study of Parents and Children (ALSPAC; Boyd et al., 2013; Fraser et al., 2013), Born in
36 Bradford (BiB; McEachan et al., 2024; Wright et al., 2013) and the Gipuzkoa, Sabadell and Valencia
37 Infancia y Medio Ambiente cohorts (INMA; Guxens et al., 2012) which were the only ones with
38 available WM assessments. These cohorts provided data from children aged 10 to 12 years (ALSPAC),
39 7 to 10 years (BiB), 6 to 8 years and 10 to 12 years (INMA). Ethics and funding aspects of each cohort
40 study are described in the supplementary materials.

41 2.2 Study variables

42 2.2.1 Exposures

43 The residential environment of each participant the year when the WM assessment was conducted
44 was characterised via two complementary residential greenness metrics widely used in the field (Labib
45 et al., 2020; Nordbø et al., 2018); NDVI and the availability of green spaces > 5,000 m². The NDVI is a
46 greenness measure derived from satellite imagery. We used imagery corresponding to in the maximum
47 vegetation period from the Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper
48 Plus (ETM+), and Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) with 30m x
49 30m resolution was used to determine the surrounding greenness. NDVI scores range from 1 to +1
50 (Tucker, 1979), with 1 being the maximum greenness level. Negative NDVI values correspond to water,
51 snow and other non-vegetated surfaces and were removed to calculate the final scores (Peters et al.,
52 2022; Zhang et al., 2020).

53 Availability of major (>5000 m²) greenspace was computed using Urban Atlas. For ALSPAC and
54 the INMA 6 to 8 years follow-up, we used the following land cover classes within Urban Atlas
55 (Copernicus, 2006) : 14100 (Green urban areas), 30000 (Forests and semi-natural areas), and 20000
56 (Agricultural areas). In the case of BiB and INMA 10 to 12 years follow-up, a wider set of classes
57 (Copernicus, 2012) were included: 14100 (Green urban areas), 21000 (Arable land [annual crops]),
58 22000 (Permanent crops), 23000 (Pastures), 24000 (Complex and mixed cultivation patterns), 25000
59 (Orchards), 31000 (Forests), and 32000 (Herbaceous vegetation associations).

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

65 2.2.2 Mediator

66 Individual residential exposure to NO₂ also during the year of WM assessment was estimated using
67 the land use regression (LUR) models. For ALSPAC, we resorted to the models created for the Effects
68 of Low-Level Air Pollution: A Study in Europe project (ELAPSE; (De Hoogh et al., 2018). For BiB and
69 INMA, we used the LUR models developed in the European Study of Cohorts for Air Pollution Effects
70 (ESCAPE; Beelen et al., 2013; Estarlich et al., 2011). These models explained a high proportion of the
71 observed variance in the NO₂ levels measured in the air pollution campaigns conducted to validate
72 them (the following coefficients are R² scores); ALSPAC = 0.54, BiB = 0.77, INMA-Gipuzkoa = 0.51,
73 INMA-Sabadell = 0.77, and INMA-Valencia = 0.73.

74 2.2.3 Outcome

75 Participants' WM performance was measured in each of the cohort and follow-ups included in the
76 study. In ALSPAC and INMA (6 to 8 and 10 to 12 years), WM was measured with N-back tests, a
77 computerized cognitive task consisting of the recall of a previously presented stimulus (i.e., number).
78 The stimuli appeared on the screen one at a time, and the participant was instructed to press a button
79 if the current stimulus was the same as the second to last stimulus shown (2-back test). A WM score
80 was calculated via the estimation of the d prime (d') index, a measure derived from signal detection

81 theory that allows the distinction of signal from noise. Measures of d' were calculated for each trial as
82 follows: $d' = z(\text{hit rate}) - z(\text{false alarm rate})$, a higher d' indicating better detection, and thus, a more
83 accurate performance (Deserno et al., 2012; Stanislaw, 1999). The task was created using the
84 psychology experiment software E-Prime version 2.0 (Psychology Software Tools Inc, Pittsburgh, PA,
85 USA).

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

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

97 2.2.4 Covariates

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

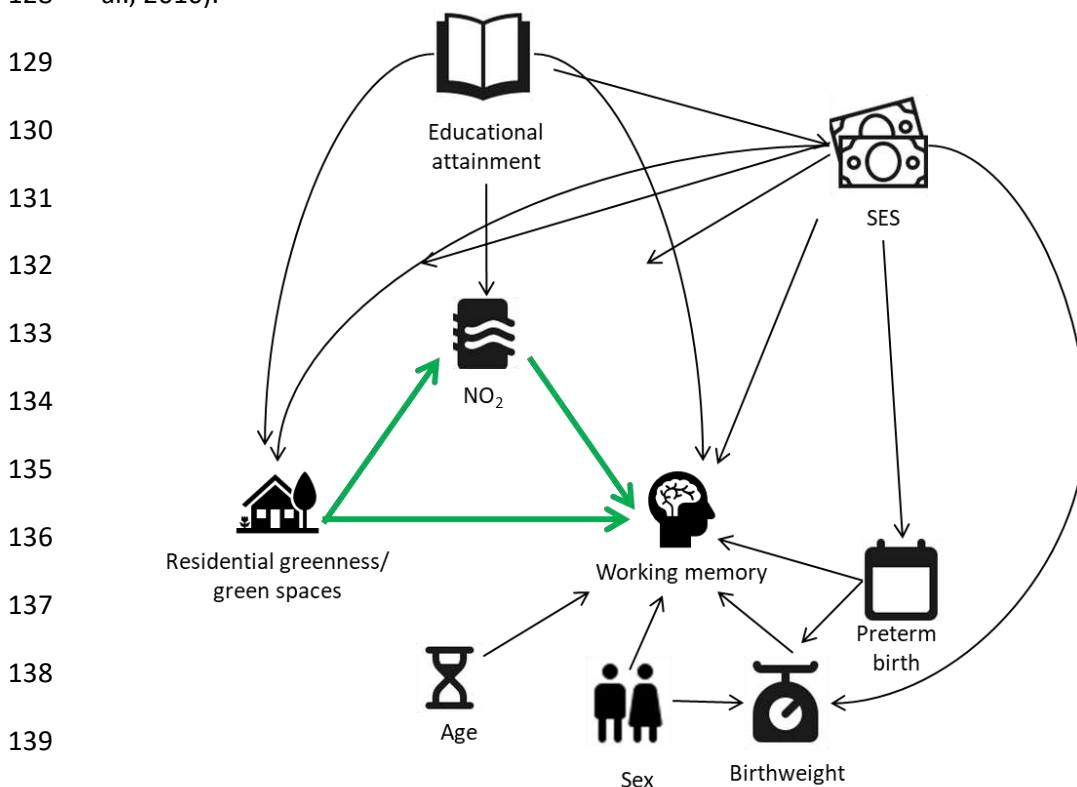
106 2.4 Data analysis

107 The dataset was analysed using R software v.4.0.3 (R Core Team, 2022). After estimating descriptive
108 statistics, we applied the principles of robust causal inference to select the covariates to be included
109 in the statistical models. We started by adapting the Direct Acyclic Graph (DAG) from a previous study
110 on greenness and WM (Subiza-Pérez et al., 2023; see Figure 1) and validating it separately for each
111 cohort and follow-up, following the procedure described elsewhere (Ankan et al., 2021; Subiza-Pérez
112 et al., 2024, 2023) and using R packages dagitty (Textor, 2020; Textor et al., 2017) and lavaan (Rosseel,
113 2012). In line with these previous studies, we considered testable implications as unmet when their
114 associated p-values were lower than 0.05 and the r -scores larger than 0.20. The minimum adjustment
115 sets of variables were identified via the dagitty function `adjustmentSets()`. This process was applied to
116 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).

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

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



139
140
141 **Figure 1.** DAG explaining the relationship between exposure to residential green
 142 space and working memory. Arrows highlighted in green correspond to the effects
 143 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. NO₂ = nitrogen dioxide.

144 3. Results

145 3.1 Sample description and DAG validation

146 The analytical samples comprised 6,760 participants distributed among the four study samples (see
 147 Table 1). These samples were evenly distributed in terms of sex, except for INMA 6 to 8 years follow-
 148 up sample in which a greater proportion of males was observed. Preterm birth was below the 5% of
 149 the samples and was slightly higher in the British samples. In terms of maternal educational

150 attainment, we found relevant differences between the samples. Most ALSPAC mothers were
151 moderately educated whereas those included in the BiB sample had low educational attainment.
152 Mothers in INMA clustered among the medium and high levels of educational attainment. Regarding
153 greenspace availability, most of the participants (>70%) lived within 300 m of a green space larger than
154 5,000 m², but that figure was higher for those participants in the Spanish samples. In contrast, the
155 observed NDVI values were larger in ALSPAC and BiB than INMA. Concentrations of NO₂ were similar
156 among the samples, although a greater between-participant variability was observed in the INMA
157 samples.

158 None of the testable assumptions implied in the DAG obtained r-coefficients above 0.20 and
159 p-values below 0.05 (see Appendix I) in the ALSPAC, BiB and INMA 10 to 12 years follow-up samples,
160 so the initial DAG was considered correct for these samples. However, two testable implications were
161 unmet in the case of the INMA 6 to 8 years follow-up; “greenness metric ⊥ age” and “NO₂ ⊥ age”,
162 which indicated that exposures were not independent of the age when the WM test was conducted.
163 We updated the study DAG with these relationships (see Supplementary Figure 1) and extracted the
164 minimum set of adjustment variables for the total association models, which was composed of
165 maternal education and family income for all the models. In addition, age was included in the models
166 involving the INMA 6 to 8 years follow up sample. For the direct association models, the adjustment
167 set also included NO₂.

168 *3.2 Separate models*

169 Table 2 shows the results of the separate linear regression models. We found a consistent positive
170 association between NDVI and WM scores in BiB and INMA 6 to 8 years cohorts; participants living in
171 greener residential settings scored higher in the computerized WM task. In the case of BiB, we also
172 observed that availability of green spaces was positively associated with the outcome. However, we
173 could not confirm the mediation via NO₂ as all the indirect association coefficients but one fell above
174 the p = 0.05 threshold. For the cohorts and follow-ups involving older participants (i.e., ALSPAC and
175 INMA 10 to 12 years), none of the models revealed statistically significant associations, so neither
176 residential greenness nor green space availability predicted WM scores. See the graphical depictions
177 of these associations, along with the distribution of residuals in Supplementary figures 2A and 2B.

178 *3.3 Meta-analysis*

179 Figure 2 and Supplementary Figure 2 show the results of the meta-analysis. The only integrated
180 estimate showing a statistically significant association was that of NDVI 100 m [0.48, (95%CI = 0.05 –
181 0.91)], indicating greater WM scores for those participants living in greener areas. The rest of the
182 combined estimates, albeit suggestive of a positive association, did not reach statistical significance.
183 Meta-analytic estimates revealed a high level of heterogeneity between the individual studies ($I^2 = 45$
184 – 76%). The forest (Figure 2) and the funnel (Supplementary Figure 3) plots confirmed what was found
185 in the earlier stage of the analysis as they showed how the connection between residential greenness
186 and green space availability was stronger and statistically significant only in BiB and the INMA 6 to 8
187 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)

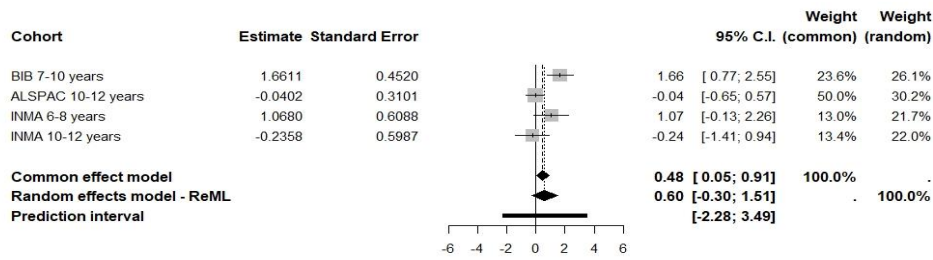
Note: BW = Birth Weight, EUSILC = index of total disposable family income. NDVI 100, 300, and 500: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers. NO₂ = Nitrogen dioxide, WM = Working Memory. 'Green availability' refers to major greenspace (>5000 m²) within 300m of home address, including green urban areas, forests, and agricultural areas.

Table 2.
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

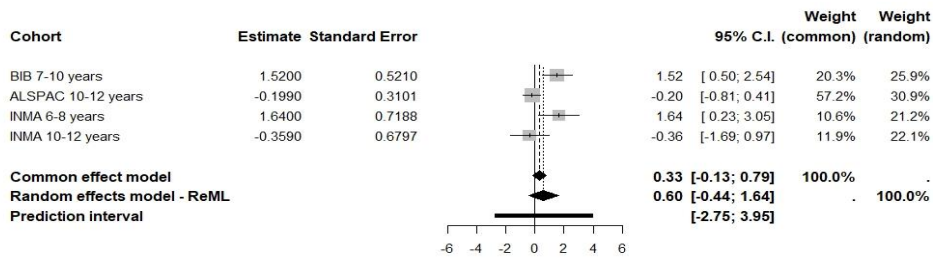
Note: NDVI 100, 300, and 500: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers. 'Green availability' refers to major greenspace (>5000 m²) within 300m of home address, including green urban areas, forests, and agricultural areas. Covariates: maternal educational attainment and family 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.

1



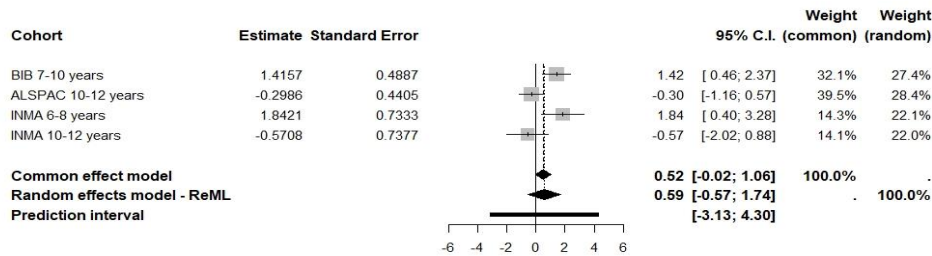
Heterogeneity: $I^2 = 75.0\%$, $\tau^2 = 0.6084$, $p = 0.007$
 Test for overall effect (common effect): $z = 2.18$ ($p = 0.029$)
 Test for overall effect (random effects): $z = 1.31$ ($p = 0.191$)
 Estimates of the <NDVI 100 m> total effect on working memory

2



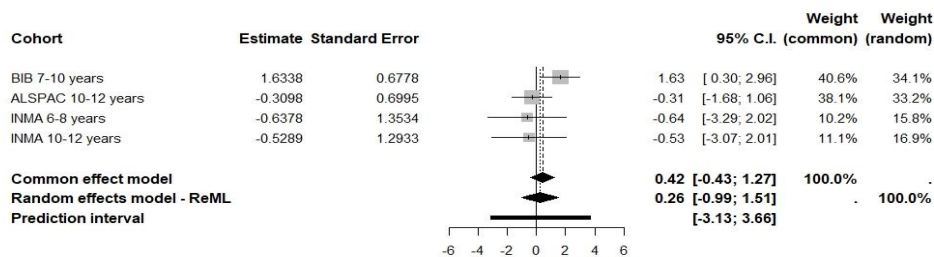
Heterogeneity: $I^2 = 76.0\%$, $\tau^2 = 0.8221$, $p = 0.006$
 Test for overall effect (common effect): $z = 1.39$ ($p = 0.165$)
 Test for overall effect (random effects): $z = 1.13$ ($p = 0.259$)
 Estimates of the <NDVI 300 m> total effect on working memory

3



Heterogeneity: $I^2 = 75.5\%$, $\tau^2 = 1.0186$, $p = 0.007$
 Test for overall effect (common effect): $z = 1.87$ ($p = 0.061$)
 Test for overall effect (random effects): $z = 1.00$ ($p = 0.319$)
 Estimates of the <NDVI 500 m> total effect on working memory

4



Heterogeneity: $I^2 = 44.9\%$, $\tau^2 = 0.7329$, $p = 0.142$
 Test for overall effect (common effect): $z = 0.98$ ($p = 0.329$)
 Test for overall effect (random effects): $z = 0.41$ ($p = 0.680$)
 Estimates of the <Green Availability> total effect on working memory

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).

189 *4. Discussion*

190 We aimed to produce new scientific evidence that could contribute towards a consensus on the
191 associations between residential greenness and WM during childhood and pre-adolescence. This is
192 needed because the current epidemiological evidence is mixed. The systematic review by Buczyłowska
193 and colleagues (2023) indicated that only four out of seven of the published observational studies in
194 the field were able to statistically confirm the hypothesised protective greenness-WM links during
195 childhood and adolescence. Similarly, a systematic review and meta-analysis published after the
196 conduction of the analysis presented in this piece, and therefore not described in the introduction of
197 this paper, synthesized the results of 22 correlational studies using residential greenness metrics and
198 found no overall association between those and cognitive performance in children and adolescents
199 (Nguyen and Walters, 2024). In line with this picture, our results are far from consistent. We found
200 that residential greenness, in the form of NDVI, was positively associated with WM scores but only for
201 those participants between 6 and 10 years of age. However, the resulting coefficient showed a high
202 degree of heterogeneity, which limits its generalizability. For older groups, NDVI values did not predict
203 WM scores. Moreover, the availability of green spaces near the household showed a beneficial
204 association with WM memory in BiB but that could not be confirmed in the other cohorts. Finally, and
205 contrary to theoretical expectations (Markevych et al., 2017) and previous studies (Dadvand et al.,
206 2015), we did not find support for the air pollution reduction pathway.

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

215 In order to test this possibility, we reviewed the studies compiled by Buczyłowska and
216 colleagues (2023) and the one by Fernandes et al. (2023) to see whether the pattern of statistically
217 significant vs non-significant results aligned with the childhood-adolescence gap suggested here. The
218 age of participants in the studies that reported significant beneficial associations greenness and/or
219 green spaces are as follows: 4 to 6 years (Dockx et al., 2022), 7 to 13 years (Dadvand et al., 2015), 9 to
220 15 years (Maes et al., 2021) and 11 years (Flouri et al., 2019). On the other hand, those not reporting
221 statistically significant results analysed data from samples composed of participants 5 to 18 years
222 (Reuben et al., 2019), 6 to 11 years (Fernandes et al., 2023; Julvez et al., 2021) and 13 to 17 years
223 (Bijnens et al., 2022). The picture that emerges from this revision, also supported with the results of
224 our work, is that the statistically significant and non-significant results do not cluster by age and
225 therefore more studies are needed to establish a scientific consensus.

226 *4.1 Study strengths and limitations*

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

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

239 However, there are some limitations that need to be acknowledged when interpreting our
240 results and that are pervasive in this area of research. We focused on the home environment and
241 therefore neglected other relevant environments that may have an impact on behaviour and
242 development, such as the school or leisure areas. This has been referred to as the *uncertain geographic*
243 *context problem* (Kwan, 2012, 2009). Moreover, and in line with Labib and colleagues (2020), our study
244 does not account for the frequency and duration of residential green space use, if any, and their quality,
245 design and safety features. In terms of the outcome, the measurement of WM was not fully consistent
246 across cohorts. We encourage future researchers in this area to employ a consensual strategy that could
247 lead to more homogenous evidence. Furthermore, given that we studied the cross-sectional
248 associations between greenness metrics and WM scores we cannot make inferences about potential
249 long-term effects (e.g., early childhood exposure). Despite the fact that we could not control for it due
250 to the nature of our greenness metrics (i.e., NDVI values corresponding to the period of maximum
251 vegetation), one of the anonymous reviewers insightfully pointed out that the potential confounding
252 effects of seasonality, given the season variations observed in both greenness (Klimavičius et al., 2023;
253 Naif et al., 2020) and cognitive performance (Hohm et al., 2024; Meyer et al., 2016) metrics. We
254 consider that future research on greenness and executive functions should consider this aspect. We
255 did not explore pathways other than the reduction of NO₂ concentrations, and therefore we lack
256 specific information about other pollutants (e.g., particulate matter) and other potential pathways
257 such as the promotion of physical activity or social cohesion (Markevych et al., 2017). Nevertheless,
258 from a formal point of view, the potential association through those other pathways are included
259 within the direct association estimates. We used a complete case analysis approach, since there were
260 no statistically significant differences between the missingness of covariates and the exposure or the
261 outcome (Missing at Random-MAR hypothesis). Our choice led to unbiased estimates, although it
262 resulted in a potential loss of statistical power. In this context, it also needs to be acknowledged that,
263 given that our participants enrolled in the cohort study and the subsequent follow-ups voluntarily, our
264 study might be affected by selection bias. Despite some previous works using part of the available
265 residential greenness and WM data within the A EU Child Cohort Network consortium study
266 (Fernandes et al., 2023; Subiza-Pérez et al., 2023), this study is the first one using all the data available
267 in the consortium. Both the analysis of the BiB and ALSPAC datasets, and the meta-analytic approach
268 is original to the study presented here.

269 5. Final remarks

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

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