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Residential green and blue spaces and working memory in children aged 6–12 years old. Results from the INMA cohort

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A B S T R A C T

Availability of green and blue spaces in the area of residence has been related to various health outcomes during childhood, including neurodevelopment. Some studies have shown that children living in greener and/or bluer areas score better on cognitive tasks although the evidence is inconsistent. These protective effects are hypothesized to occur in part through reductions in air pollution exposure and odds of attention-deficit/hyperactivity disorder (ADHD). This study analysed the effects of residential green and blue spaces on working memory of children in the Spanish INfancia y Medio Ambiente (INMA) birth cohort and the potential joint mediating role of air pollution and ADHD. The study samples were composed of 1738 six-to eight-year-olds (M = 7.53, SD = 0.68, 49% female) and 1449 ten-to twelve-year-olds (M = 11.18, SD = 0.69, 50% female) living in Asturias, Gipuzkoa, Sabadell or Valencia, Spain. Individual Normalized Difference Vegetation Index (NDVI) values in 100-, 300- and 500-m buffers and availability of green and blue spaces >5000 m^2 in 300-m buffers were calculated using Geographic Information Systems software. Individual NO_2 values for the home environment were estimated using ESCAPE's land use regression models. ADHD diagnosis was reported by participants' parents via a questionnaire. Working memory was measured with numbers and colours (in the younger group only) N-back tests (2- and 3-back *d'*). Mixed-effects models informed of the beneficial effects of NDVI in a 300-m buffer on numerical working memory in the younger sample although the results were not consistent for all *d'* scores considered and failed to detect significant effects through the candidate mediators. Availability of major

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blue spaces did not predict working memory performance. Provision of green spaces may play a role in children's working memory but further research is required.

1. Introduction

Working memory (WM) is an executive function that emerges from the interaction between memory and attention and allows us to maintain and manipulate information for short periods of time (Cowan, 2014; Shelton et al., 2010). Information maintenance and management are key for dealing with cognitive tasks such as language comprehension, learning, reasoning, and problem-solving (Baddeley, 1992; Vuontela et al., 2003). Stored information can be numerical, verbal, chromatic, or spatial, depending on the nature of the content to be stored (e.g., numbers, words, or colours). Various biological and developmental factors have been associated with WM performance during childhood. For instance, children born preterm scored lower on WM tasks in studies conducted in Finland and the UK (Fitzpatrick et al., 2016; Saavalainen et al., 2007) and there is also some evidence of sex-related differences (Voyer et al., 2021). Neurodevelopmental conditions such as attention-deficit/hyperactivity disorder (ADHD) (Arrington et al., 2022) and autism (Hill, 2004) may also impair performance in WM tasks. In the socioeconomic sphere, WM scores have been observed to be lower in children of disadvantaged families (Mooney et al., 2021) and higher in those born to mothers with higher levels of education (Dadvand et al., 2015; Forns et al., 2014). Most epidemiological evidence on WM development during childhood comes from cross-sectional studies that tend to group children of different ages (Yaple and Arsalidou, 2018); however, a couple of recent studies have addressed this question from a longitudinal perspective (Ahmed et al., 2022; Reynolds et al., 2022) and have shown that numerical WM grows rapidly during childhood, experiences a period of latency in early adolescence (10–13 years) and observes a brief second period of growth in middle adolescence. Nevertheless, research by Demetriou et al. (2014) suggested that not all modalities of WM (i.e., verbal, numerical, and visuospatial) develop following the same pattern (see also Cowan, 2016).

In recent years, there has been a growing interest in the impact of environmental exposures on the development of executive functions during childhood. In line with this emerging body of literature, we wanted to analyse the effects of residential greenness and blueness on working memory performance during childhood.[1] By so doing, we aimed at increasing available evidence on the matter and help to stablish a scientific consensus. In the following lines we will review the evidence on both the school and residential settings together in order to give a more comprehensive description of available evidence. An early study by Dadvand et al. (2015) showed that greenness at school exerted a positive influence on WM development over 12 months in Spanish children aged 7–10 years; however, they found no association with residential greenness, as measured by the average Normalized Difference Vegetation Index (NDVI). In a study involving 1300 mother-child pairs from six European birth cohorts, Julvez et al. (2021) explored the effects of prenatal NDVI and green and blue space availability in residential and school contexts and did not find any associations with WM scores. These two studies have recently been included in a systematic review (Buczyłowska et al., 2023) together with five other observational studies on greenness and WM. These studies, categorized as having a low or probably low risk of bias by the authors of the review, were not consistent: four showed significant protective associations between greenness and WM while three did not. Only one of the observational studies included in the review analysed the relation between exposure to blue spaces and WM (Maes et al., 2021) which makes the need for further studies even more evident in the blue spaces literature.

1.1. Pathways linking residential greenness and blueness to working memory

Exposure to air pollution has been negatively related to WM and attention. For instance, higher NO_2 concentrations in the school environment were linked to lower WM scores (Alemany et al., 2018; Forns et al., 2017; Sunyer et al., 2015) in Spanish children aged 7 to 10. Exposure to NO_2 was also linked to attention scores in two other Spanish studies (Sentís et al., 2017; Sunyer et al., 2017). Greener areas would be less polluted due to the deposition of pollutants (Liu et al., 2018), their absorption by leaves (Diener and Mudu, 2021), and their enhanced dilution due to the increased distance to emission sources (e.g., roads; Klingberg et al., 2017). Indeed, one of the proposed pathways linking the former to human health and well-being has been precisely the reduction of exposure to air pollution (Dzhambov et al., 2020; Markevych et al., 2017). Past research on residential greenness and WM has not been unaware of this possibility. Dadvand et al. (2015) reported that between 20% and 65% of their observed associations between school greenness and WM could be explained through reductions in air pollution exposure at school. However, Anabitarte et al. (2022) were not able to confirm the residential greenness-air pollution-attention pathway in their study.

Likewise, it has been hypothesized that blue spaces, such as beaches, rivers, and lakes, could have a positive effect on human health (White et al., 2020), although there have been relatively few studies (Gascon et al., 2017). While White et al. (2020, p. 5) asserted that blue spaces were unlikely to affect air pollution levels to the same extent as green spaces, this possible pathway has been mentioned in the blue spaces literature (Georgiou et al., 2021). Specifically, while not all the processes involved in *green* air pollution reduction can take place in blue settings (i.e., absorption by leaves), pollutants could be deposited in water (Pryor and Barthelmie, 2000) and greater dilution due to increased distance to emission sources could also be expected. Indeed, recent studies have considered this in wetlands and lakes (Liu et al., 2016, 2018; Qiu et al., 2015).

Although evidence is still growing and is not unequivocal, these exposures also seem to be related to the symptoms and diagnosis of ADHD. Some authors have explained the potential effects of greenness on ADHD via several pathways; psychological restoration and stress recovery, and increased microbial diversity (Thygesen et al., 2020). A recent review of studies on greenness and child behaviour included 15 studies on the presence of ADHD symptoms and 10 on the confirmed diagnosis of the disorder (Zare Sakhvidi et al., 2022). Most of the first group of studies found a negative association between residential greenness metrics and ADHD symptoms. Regarding ADHD diagnosis, results were less consistent, three reporting a protective association between greenness and ADHD diagnosis whereas the others yielded null

[1] Given that disadvantaged socioeconomic groups tend to live in areas of lower environmental quality (Gerrish and Watkins, 2018; Gray et al., 2013; Reuben et al., 2019; Rigolon, 2017) and also score lower in WM tasks (Dadvand et al., 2015; Forns et al., 2014; Mooney et al., 2021), SES and education variables have to be considered as potential confounders.

[2] See also www.escapeproject.eu.

[3] Timing of assessment the variables included in the study was as follows. Child's sex, preterm birth, and birthweight, as well as maternal education were measured in the baseline assessment (2004–2008), which included the pregnancy and delivery of recruited mothers. Environmental exposures (i.e., greenness, blueness, and air pollution), working memory, ADHD diagnosis and area SES indicators were measured or calculated at every follow-up. The follow-up when children reached 6–8 years of age took place between 2012 and 2017 and the follow-up when they reached 10–12 years between 2015 and 2019.

or mixed results. In the case of air pollution, the relationship is not that clear either. Aghaei et al. (2019) reviewed 28 studies on air pollution and ADHD. Only half of the 12 studies that included a measure of NO_2 reported statistically significant relations between NO_2 exposure and ADHD. Adding to this mixed evidence, another study not included in the former review that analysed data from c. 30,000 European children indicated that exposure to air pollution during mothers' pregnancy was not associated with ADHD symptoms (Forns et al., 2018). This evidence, and the association between ADHD and WM performance (Arrington et al., 2022), invite to consider ADHD as a potential mediator between exposure to greenness/blueness and working memory performance.

The aim of this study was to analyse the effects of residential green and blue spaces on WM of children participating in the Infancia y Medio Ambiente (INMA) birth cohort and evaluate the potential joint mediating role of air pollution and ADHD. According to the evidence reviewed above, we expected that green and blue spaces would have a positive effect on WM scores and that part of these effects may happen through the reduction of exposure to NO_2 and reduced rates of ADHD. The analytic procedure we followed is fully explained in the corresponding section of the manuscript. Nonetheless, we wish to make a point about the nature of the effects we have estimated for this study, which follow the theoretical and empirical background showed above. Our statistical models show the total effects of residential greenness and blueness metrics on WM. In fact, these total effects encompass: 1. the direct effects of greenness and blueness metrics on WM (this is also independently estimated); 2. a single mediation effect with the formula "greenness/blueness → NO2 → WM"; 3. another single mediation effect: "greenness/blueness → ADHD → WM"; and 4. a sequential mediation effect with the following structure: "greenness/blueness → NO2 → ADHD → WM".

2. Methods

2.1. Sample of participants

The study sample was composed of children 6 to 8 and 10–12 years of age participating in the INMA pregnancy cohort study (Guxens et al., 2012; www.proyectoinma.org), which recruited women in the first trimester of pregnancy in public health system health centres and hospitals in four regions of Spain, specifically, in Asturias, Gipuzkoa, Sabadell, and Valencia. These four areas correspond to two different climate and biogeographic regions (Dadvand et al., 2012), namely, Eurosiberian (Asturias and Gipuzkoa) and Mediterranean (Sabadell and Valencia). Women were invited to participate if they were 16 years old or older, had a singleton pregnancy, had not received assisted reproduction treatment, planned to give birth in their referral hospital, and were able to communicate in at least one of the official languages in their corresponding region. Between 2004 and 2008, a total of 2644 women were recruited (Asturias, 494; Gipuzkoa, 638; Sabadell, 657; and Valencia, 855) and, since then, they and their children have been regularly followed up. In this paper, we present data from the children's 6- to 8-year and 10- to 12-year follow-ups, with 1738 participants (Asturias, 359; Gipuzkoa, 392; Sabadell, 539; and Valencia, 448) in the first of these periods and 1449 (Asturias, 213; Gipuzkoa, 379; Sabadell, 491; and Valencia, 366) in the second. On average, they were aged 7.53 ($SD = 0.68$) and 11.18 ($SD = 0.69$) respectively at the time when their neuropsychological development was measured and the samples were balanced in terms of sex (48.79% and 50.45% were female respectively). The ethics committees of the hospitals involved in each region approved the project and informed consent was obtained from all the participants' parents in each wave.

2.2. Study variables

2.2.1. Environmental exposures

Participants' home environment was characterized via two metrics of greenness: NDVI and availability of greenspace >5000 m^2. These measures, and the buffers described below, are extensively used in the field (Nordbø et al., 2018), and partially (i.e., in relation to green space availability) based on the recommendations of the World Health Organization (2016). The NDVI is a greenness measure derived from satellite imagery obtained from Landsat 4–5 Thematic Mapper and Landsat 8 Operational Land Imager and Thermal Infrared Sensor with a resolution of 30 × 30 m in the maximum vegetation period (see Supplementary Table 1). This variable ranges from −1 to +1 (Tucker, 1979), 1 being the maximum greenness level. Negative NDVI values correspond to water. As the aim was to obtain a vegetation index during the greenest period of the year, negative NDVI values were removed before calculating the mean NDVI values in buffer zones (Peters et al., 2022; Zhang et al., 2020). For the current study, we averaged NDVI in 100-, 300- and 500-m buffers around the home address. We also included the availability of major (>5000 m^2) greenspace using Urban Atlas. Land cover classes 14100 (Green urban areas), 30000 (Forests and semi-natural areas), and 20000 (Agricultural areas) included in Urban Atlas (Copernicus, 2006) were used to estimate this exposure for the 6- to 8-year follow-up, while a wider set of classes included in Urban Atlas (Copernicus, 2012) were used for the 10- to 12-year follow-up: 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). Blue spaces were defined by considering the 50000 (Water) land cover class in both versions of the Urban Atlas and the availability of major blue spaces (>5000 m^2). The blue space size and the buffer radii were selected following previous studies (Binter et al., 2022; Nieuwenhuijsen et al., 2019)

2.2.2. Mediators

Individual residential exposure to NO_2 was estimated using the land use regression (LUR) models developed in the European Study of Cohorts for Air Pollution Effects[2] (ESCAPE; Beelen et al., 2013). The LUR model for Asturias included surface area (m^2) of high-density residential land in a 1,000-m buffer, number of households in a 5,000-m buffer, and surface area of low-density residential land in a 100-m buffer, and the one for Gipuzkoa, surface area of high-density residential land in a 1000-m buffer and industry and ports in 100-m buffers. Surface area of high-density natural land in a 5000-m buffer, population in a 500-m buffer, and surface area of high-density residential land in a 5000-m buffer were the predictor variables in the Sabadell LUR model. Finally, the Valencia model incorporated surface area of high-density residential land in 500-m buffer, number of households in a 5000-m buffer, and square of the inverse distance to the sea. Models R^2 values, which indicate the correlation between the models and the observed NO_2 values in intensive monitoring campaigns in each location, varied as follows: Asturias = 0.88, Gipuzkoa = 0.89, Sabadell = 0.90, and, Valencia = 0.91. These models were used to estimate NO_2 values for each follow-up.

The presence of an ADHD diagnosis at 6–8 and/or 10–12 years was based on report by the parents in follow-up questionnaires. At the 6- to 8-year follow-up, the parents were asked to complete a questionnaire including the following question: "*Has your child been diagnosed with ADHD?*", while at the 10- to 12-year follow-up, they were asked to indicate whether a health professional had diagnosed their child with any psychological or psychiatric condition, and if so, specify which. Children were assumed to have ADHD if their parents reported this diagnosis.

2.2.3. Outcome

Working memory was measured with N-back tests, computerized cognitive tasks consisting of the recall of a previously presented stimulus (e.g., a number, colour, or shape). Both number (measuring numerical WM) and colour (measuring chromatic WM) N-back tests were used in the 6- to 8-year-olds but only numbers were used in the 10- to 12-year-olds. The stimuli appear on the screen one at a time, and the participant is instructed to press a button if the current stimulus is the same as the previous one (1-back; not included in this study), the second to last (2-back), or the third to last (3-back). The cognitive load of the task and, therefore, the demand on WM, increases accordingly. In this study, participants completed 2- and 3-back number tests at both follow-ups and also 2- and 3-back colour tests at the 6- to 8-year follow-up. N-back tests were administered to participants following a common protocol defined for the cohorts by trained research assistants in the data collection sessions that took place in participants' schools in Gipuzkoa and referral hospitals and health centres in Asturias, Sabadell, and Valencia. For each block separately, we calculated the overall accuracy including both hits and correct rejections and *d* prime (*d'*), 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).

2.2.4. Covariates[3]

Based on the available literature, a set of variables was selected as potential covariates for this study: sex of the child (female/male), age when the WM test was conducted, preterm birth (<37 weeks of pregnancy, yes/no), birthweight (in grams), maternal education (primary, secondary, university) as an indicator of household socioeconomic status (SES) and area SES (1-most deprived end to 5- least deprived) based on the deprivation index developed in the MEDEA 2011 project (Domínguez-Berjón et al., 2008). This index is a composite census tract-based measure of five area indicators, namely, rates of 1) unemployment, 2) manual work, 3) short-term contract work, and 4) and 5) respectively, insufficient educational attainment overall and among young people.

2.3. Data analysis

The dataset was analysed using R software v.4.0.3 (R Core Team, 2022). After estimating descriptive statistics, we applied a three-steps procedure to select the covariates to be included in the regression models. First, to represent our literature review-based assumptions concerning the natural process underlying WM, we developed a direct acyclic graph (DAG) (Fig. 1) (Pearl, 2009; Tennant et al., 2021). Such a DAG was used independently for the 6–8 and 10–12 year analyses. Second, we tested the validity of the DAG using the R packages dagitty (Textor et al., 2017, 2020) and lavaan (Rosseel, 2012). This requires the identification of the testable implications of the DAG, for which we applied the *d*-separation criterion (Pearl, 1986; Verma and Pearl, 1990) via the dagitty function impliedConditionalIndependencies(). Testable implications are pairwise marginal and conditional independencies implied by a given DAG (Elwert, 2013): if these properties of the joint distribution are not satisfied by the data, we find reason to reject, or possibly modify, the model (Chen et al., 2014). Thus, since our dataset is a combination of categorical and continuous data, we computed the polychoric correlation matrix of the dataset (Ankan et al., 2021) through the lavaan function lavCor(), and then applied the test itself of the aforementioned conditional independencies against the correlation matrix using the dagitty function localTests() (Textor, 2020). Testable implications were considered unmet when *p*-values were found to be lower than 0.05 and *r*-scores larger than 0.20; unmet implications were taken to be an indication of missing relationships and subsequently included in the DAG. Having tested the validity of the DAG, we proceeded to the third and last step: the identification of covariate adjustment sets by applying a complete generalized adjustment criterion (Perković et al., 2015; Van Der Zander et al., 2014). Covariate adjustment sets are sets of covariates that permit unbiased estimation of effects from observational data by blocking biasing paths and leaving open the

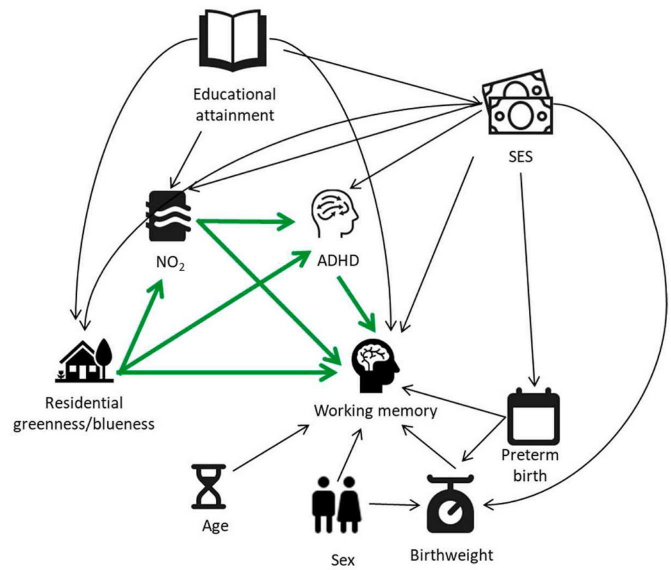

Fig. 1. DAG explaining the relationship between exposure to residential green and bluespaces and working memory. The arrows indicate causal paths. All the relationships were defined based on previous literature. Arrows highlighted in green correspond to the effects of interest for this study. SES = area socioeconomic status, NO_2 = nitrogen dioxide, and ADHD = attention deficit/hyperactivity disorder.

paths of interest for the study, and we obtained these sets using the dagitty function adjustmentSets(). Once this issue was solved, we proceeded to the estimation of the total and direct effects of the exposure variables on outcomes (in this case, WM scores). Indirect effects would be the difference between total and direct effects. For this purpose, we assumed linearity (a DAG is a non-parametric object) and applied mixed-effects modelling with the function lme() of the R package nlme (Pinheiro et al., 2022), for which we used <cohort> as a random factor and the corresponding sets of covariates as adjustment sets. We only interpreted the fixed effects of exposures on outcomes, since the role of covariates is just to act as adjustment sets, and hence, their coefficients are not interpretable. We followed the same procedure to estimate the associations between the two mediators (i.e. NO_2 and ADHD) and the working memory scores obtained by the participants in each follow-up. All the statistical analyses here described were conducted using the complete cases (i.e. without missing values on study variables) in each follow-up, which meant 933 participants for the 6–8 years follow-up and 1041 participants for the 10–12 years one. Finally, we used lme () to fit longitudinal mixed models in order to analyse the total effects of greenness and blueness over time on d2 and d3 number scores. The sample used for each of the aforementioned models, determined by the number of complete cases at each follow-up, is as follows: 933 participants for the 6–8 years models, 1041 for the 10–12 years models and 648 for the longitudinal models.

3. Results

Among the mothers of the children aged 6 to 8 (see Supplementary Table 2), a third had completed secondary education and nearly a third had a university degree. More than half of the participants lived in areas with high SES (quintiles 1 and 2), whereas the most challenged quintiles were underrepresented (3.34%). Twenty (1.15%) and 122 (8.42%) children had been diagnosed with ADHD before each of the follow-ups. With regard to the environmental conditions, most participants lived within 300 m of a green space, while only a fifth had a blue space nearby. NDVI values ranged from 0.20 to 0.49, being slightly lower in the Sabadell and Valencia cohorts. Air pollution levels were comparable in all the cohorts but that of Sabadell, where levels were higher. Children scored higher in numerical than colour n-back trials, and lower scores were obtained in 3- than 2-back back trials. Among the 10- to 12-year-olds (see Supplementary Table 3), the proportion whose mothers had secondary or university education was higher, but area SES and environmental exposures were similar to those described above for the younger sample. Again, WM scores were higher in the 2-back trials and participants performed better at this stage than in the previous follow-up.

3.1. Estimation of effects

Not all the testable implications derived from the DAG shown in Fig. 1 were met in the study samples. Table 1 and Supplementary Fig. 1 show the results of the localTest() function for models with NDVI in a 100-m buffer and d' in the colour 2-back task. To avoid redundancy, results of checking testable implications for the rest of the models are not described in this paper but will be available on request. In the case of the models for the 6- to 8-year-olds, the testable implications "age ⊥ NO_2" and "age ⊥ green exposure"[4] were not met and, therefore, they were included in a new version of the DAG. This meant that the minimum adjustment set of covariates included age, area SES, and maternal education for the total effects and those three plus ADHD diagnosis and NO_2 for the direct effects models. In the sample of 10- to 12-year-olds, "age ⊥ area SES" showed an r score >0.20 across all the exposure models. "Age ⊥ blue exposure" was unmet in the blue space availability models. This implied the use of area SES and maternal education to estimate the total effects of the exposure on the outcome plus ADHD and NO_2 for the direct effects. Models including availability of blue space as a predictor variable were additionally adjusted for age.

Table 1
r scores resulting from checking the testable implications for a model using NDVI as a predictor and *d'* in the colour 2-back task as the outcome using the localTest () function in the dagitty R package.

Testable implication	*r*	*p-value*	Lower CI (2.5%)	Upper CI (97.5%)
ADHD⊥Age	−0.077	0.018	−0.14	−0.01
ADHD⊥ Maternal ed. | area SES, NDVI 100, NO_2	0.001	0.981	−0.06	0.07
ADHD⊥ BW | area SES	−0.003	0.923	−0.07	0.06
ADHD⊥ PTB| area SES	−0.021	0.516	−0.09	0.04
ADHD⊥ Sex	−0.002	0.943	−0.07	0.06
Age ⊥ area SES	0.125	0.000	0.06	0.19
Age ⊥ Maternal ed.	−0.053	0.105	−0.12	0.01
Age ⊥ NDVI 100	0.376	0.000	0.32	0.43
Age ⊥ NO_2	−0.503	0.000	−0.55	−0.46
Age ⊥ BW	−0.018	0.588	−0.08	0.05
Age ⊥ PTB	0.095	0.004	0.03	0.16
Age ⊥ Sex	0.054	0.098	−0.01	0.12
SES ⊥ Sex	0.027	0.409	−0.04	0.09
Maternal ed. ⊥ BW | area SES	−0.009	0.791	−0.07	0.06
Maternal ed. ⊥ PTB| area SES	0.052	0.113	−0.01	0.12
Maternal ed. ⊥ Sex	0.029	0.381	−0.04	0.09
NDVI 100 ⊥ BW | area SES	0.058	0.076	−0.01	0.12
NDVI 100 ⊥ PTB| area SES	0.047	0.149	−0.02	0.11
NDVI 100 ⊥ Sex	0.059	0.070	0.00	0.12
NO_2⊥ BW | area SES	−0.007	0.821	−0.07	0.06
NO_2⊥ PTB| area SES	−0.081	0.013	−0.14	−0.02
NO_2⊥ Sex	−0.027	0.406	−0.09	0.04
PTB⊥ Sex	−0.010	0.768	−0.07	0.05

Note: PTB = preterm birth, BW = birth weight, area SES = area socioeconomic status, NO_2 = nitrogen dioxide, and ADHD = attention-deficit/hyperactivity disorder. A *r* coefficient larger than 0.20 and with *p*-value <.05 indicates that the testable implication is unmet. This means that the original DAG did not specify a relationship between two variables that actually exists in the dataset. To correctly apply the d-separation criterion to select the minimal adjustment set of covariates, which is the final aim of the DAG validation process; unspecified relationships need to be included in a new version of the DAG by adding the arrows. If those specifications were not added to the new version of the DAG and we used the previous DAG to select the minimal adjustment set, the effect estimates might be biased because not all the biasing paths would be effectively blocked.

Most of the models we fitted with the 6- to 8-year-olds sample showed effects in the expected direction, but only one was statistically significant (Table 2): NDVI in a 300-m buffer was positively associated with *d'* values for the 2-back number tasks. We found some marginally significant effects ($p < .10$) of NDVI in a 100-m buffer on 3-back colour scores and of NDVI in a 500-m buffer on the 2-back number tasks. In the three cases, both total and direct effects obtained a similar *p*-value, indicating that both were similarly relevant in statistical terms. The total effects coefficients were lower than those for the direct effects in all the situations where the exposure coefficients had *p*-values lower than 0.10, but due to the fact that their confidence intervals overlapped, we did not find any evidence of mediation through the proposed mediators. The availability of green or blue spaces within 300 m of the home address had no effect on performance in any of the tasks.

As shown in Table 3, the results for the 10- to 12-year-olds revealed only two total effects with p-values less than 0.10, again suggestive of a trend but not statistically sound. The first of them, consistent with what was found in the younger sample, indicated that higher scores for NDVI in a 300-m buffer predicted a greater WM performance in the 2-back number task. Contrary to theoretical expectations, however, living within the vicinity of a major green space led to a worse performance in the 3-back number task. Supplementary Table 4 shows the associations between the mediators and the working memory scores. As can be seen in said table, no association could be confirmed between NO_2 values and WM scores. With regard to ADHD, and only in the 10–12 years follow-up sample, it was negatively associated with scores in the 2 and 3-backs trials.

The results of the longitudinal models fitted to analyse the associations between green and blue metrics with d2 and d3 numbers scores can be seen in Supplementary Tables 5 and 6. The obtained pattern of results is comparable to the one seen in the cross-sectional models although the coefficients had lower p-values in the case of NDVI. NDVI scores, regardless of the buffer size, were positively associated with d2 and d3 numbers scores and showed statistically significant interaction effects with time. These effects indicate that said association disappears in the second follow-up. Neither main effects nor interaction effects were detected for green space availability and despite the main effect of blue space availability was non-significant, a statistically significant interaction with time was observed.

4. Discussion

This study sought to improve our understanding of the effects of exposure to residential green and blue spaces in the WM of children. We also aimed to explore whether or not part of those effects, if any, occurred through the differences in mediators of air pollution (Dadvand et al., 2015; Markevych et al., 2017) and ADHD diagnosis (Donovan et al., 2019; Thygesen et al., 2020; Zare Sakhvidi et al., 2022). To do so, we built on previous scientific evidence and defined a comprehensive DAG which accounted for the relationships among the exposures and the outcome of interest. The application of the principle of *d*-separation and graphical adjustment criteria to this DAG allowed us to find out the minimum sets of adjustment variables to estimate the total and direct effects of green and blue spaces on WM scores. For the 6- to 8-year-olds, we found that NDVI scores in a 300-m radius from participants' homes predicted higher WM values in the 2-back number task, although the pattern was not observed in the other buffer and outcome combinations.

[4] ⊥ indicates independence between the terms at each side of the symbol. Therefore, the testable implications mentioned in the text should be read as follows: "age of the children is independent from their NO_2 values" and "age of the children is independent from green exposure metrics".

Table 2
Total and direct effects of residential greenness and blueness metrics on working memory in the 6- to 8-year-olds (n = 933).

Exposure	Outcome	Kind of effect	Covariate adjustment set	Estimate	95% CI	*t*	*p*-value
NDVI 100	d2 colours	Total effect	Age, area SES, maternal education	0.48	(-0.15, 1.11)	1.5	0.134
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.32	(-0.40, 1.05)	0.88	0.381
	d3 colours	Total effect	Age, area SES, maternal education	0.47	(-0.02, 0.96)	1.89	0.060
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.56	(-0.01, 1.12)	1.96	0.050
	d2 numbers	Total effect	Age, area SES, maternal education	0.44	(-0.25, 1.12)	1.25	0.211
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.36	(-0.43, 1.16)	0.89	0.372
	d3 numbers	Total effect	Age, area SES, maternal education	0.07	(-0.51, 0,66)	0.24	0.807
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.01	(-0.68, 0.68)	0.01	0.992
NDVI 300	d2 colours	Total effect	Age, area SES, maternal education	0.44	(-0.14, 1.03)	1.49	0.137
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.27	(-0.46, 1.00)	0.73	0.465
	d3 colours	Total effect	Age, area SES, maternal education	0.25	(-0.21, 0.72)	1.06	0.287
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.29	(-0.29, 0.87)	0.97	0.330
	d2 numbers	Total effect	Age, area SES, maternal education	0.69	(0.04, 1.34)	2.10	0.036
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.85	(0.06, 1.64)	2.10	0.036
	d3 numbers	Total effect	Age, area SES, maternal education	0.23	(-0.33, 0.81)	0.81	0.421
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.24	(-0.47, 0.95)	0.67	0.505
NDVI 500	d2 colours	Total effect	Age, area SES, maternal education	0.39	(-0.19, 0.96)	1.33	0.185
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.12	(-0.65, 0.89)	0.30	0.762
	d3 colours	Total effect	Age, area SES, maternal education	0.16	(-0.32, 0.63)	0.65	0.517
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.12	(-0.50, 0.74)	0.37	0.710
	d2 numbers	Total effect	Age, area SES, maternal education	0.59	(-0.06, 1.24)	1.80	0.072
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.73	(-0.10, 1.56)	1.73	0.084
	d3 numbers	Total effect	Age, area SES, maternal education	0.27	(-0.31, 0.85)	0.91	0.362
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.32	(-0.44, 1.07)	0.82	0.410

Total and direct effects of residential greenness and blueness metrics on working memory in the 6- to 8-year-olds (n = 933).

Exposure	Outcome	Kind of effect	Covariate adjustment set	Estimate	95% CI	t	*p*-value
Green avail.	d2 colours	Total effect	Age, area SES, maternal education	−0.02	(-0.28, 0.24)	−0.16	0.877
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	−0.09	(-0.37, 0.18)	−0.66	0.508
	d3 colours	Total effect	Age, area SES, maternal education	0.1	(-0.10, 0.30)	0.98	0.327
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	0.09	(-0.12, 0.30)	0.88	0.378
	d2 numbers	Total effect	Age, area SES, maternal education	−0.11	(-0.38, 0.17)	−0.75	0.453
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	−0.15	(-0.44, 0.13)	−1.05	0.294
	d3 numbers	Total effect	Age, area SES, maternal education	−0.13	(-0.36, 0.10)	−1.08	0.282
		Direct effect	Age, area SES, maternal education, ADHD, NO_2.	−0.14	(-0.38, 0.10)	−1.14	0.253
Blue avail.	d2 colours	Total effect	area SES, maternal education	0.04	(-0.22, 0.31)	0.31	0.754
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	0.04	(-0.17, 0.26)	0.39	0.700
	d3 colours	Total effect	area SES, maternal education	−0.09	(-0.29, 0.11)	−0.85	0.393
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	−0.05	(-0.23, 0.13)	−0.58	0.600
	d2 numbers	Total effect	area SES, maternal education	0.08	(-0.20, 0.36)	0.56	0.574
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	0.08	(-0.17, 0.33)	0.64	0.521
	d3 numbers	Total effect	area SES, maternal education	0.04	(-0.19, 0.27)	0.33	0.738
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	0.07	(-0.59, 0.29)	0.62	0.536

NDVI 100, 300, and 500: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers; green and blue avail.: green and blue space availability; area SES: area socioeconomic status; ADHD: attention-deficit/hyperactivity disorder.

Table 3
Total and direct effects of residential greenness and blueness metrics on working memory in the 10- to 12-year-olds (n = 1041).

Exposure	Outcome	Kind of effect	Covariate adjustment set	Estimate	95% CI	*t*	*p*-value
NDVI 100	d2 numbers	Total effect	area SES, maternal education	0.28	(-0.25, 0.82)	1.04	0.301
		Direct effect	area SES, maternal education, ADHD, NO_2	0.16	(-0.44, 0.76)	0.53	0.596
	d3 numbers	Total effect	area SES, maternal education	0.21	(-0.21, 0.64)	0.98	0.327
		Direct effect	area SES, maternal education, ADHD, NO_2	0.27	(-0.22, 0.75)	1.08	0.281
NDVI 300	d2 numbers	Total effect	area SES, maternal education	0.5	(-0.06, 1.07)	1.75	0.080
		Direct effect	area SES, maternal education, ADHD, NO_2	0.51	(-0.17, 1.86)	1.47	0.141
	d3 numbers	Total effect	area SES, maternal education	0.22	(-0.22, 0.66)	0.98	0.329
		Direct effect	area SES, maternal education, ADHD, NO_2	0.36	(-0.17, 0.90)	1.33	0.184
NDVI 500	d2 numbers	Total effect	area SES, maternal education	0.49	(-0.10, 1.09)	1.62	0.106
		Direct effect	area SES, maternal education, ADHD, NO_2	0.49	(-0.26, 1.24)	1.28	0.201
	d3 numbers	Total effect	area SES, maternal education	0.22	(-0.23, 0.68)	0.96	0.337
		Direct effect	area SES, maternal education, ADHD, NO_2	0.39	(-0.19, 0.97)	1.33	0.183
Green avail.	d2 numbers	Total effect	area SES, maternal education	−0.01	(-0.21, 0.18)	−0.14	0.889
		Direct effect	area SES, maternal education, ADHD, NO_2	−0.01	(-0.21, 0.18)	−0.12	0.905
	d3 numbers	Total effect	area SES, maternal education	−0.14	(-0.30, 0.02)	−1.68	0.093
		Direct effect	area SES, maternal education, ADHD, NO_2	−0.13	(-0.30, 0.04)	−1.51	0.132
Blue avail.	d2 numbers	Total effect	Age, area SES, maternal education	0.02	(-0.18, 0.22)	0.16	0.871
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	−0.02	(-0.17, 0.13)	−0.21	0.834
	d3 numbers	Total effect	Age, area SES, maternal education	−0.02	(-0.16, 0.12)	−0.24	0.813
		Direct effect	Age, area SES, maternal education, ADHD, NO_2	−0.02	(-0.17, 0.12)	−0.21	0.834

NDVI 100, *300*, *and 500*: Normalized Difference Vegetation Index in 100-, 300- and 500-m buffers; green and blue avail.: green and blue space availability; area SES: area socioeconomic status; ADHD: attention-deficit/hyperactivity disorder.

We did not find evidence supportive of the suggested mediation effects. For the 10- to 12-year-olds, we only found marginally significant effects showing that NDVI in a 300-m buffer increased WM scores in the numerical 2-back task and that, contrary to expectations, these scores decreased for participants living in the proximity to major green spaces. The results of the longitudinal models went in the same direction although with lower associated p-values.

Further, we did not find any support for the potential association between the availability of blue spaces and WM performance. This might be due to the fact that only 20% of the participants lived in the vicinity of a blue space larger than 5000 m^2, which could have diminished our ability to detect such effects due to a lack of sufficient environmental heterogeneity. Similar reasoning, but in the reverse direction, would apply to the availability of major green spaces, which were found in the vicinity of children's homes in 80–83% of cases in both samples. Moreover, we could not confirm the mediating role of NO_2 and ADHD. However, some studies with children have used air pollution as mediator and obtained mixed results. Dadvand et al. (2015) observed that elemental carbon mediated between greenness and working memory scores whereas reductions in NO_2 did not explain the effects of greenness on attention scores in the study by Anabitarte et al. (2022). In our study, we failed to confirm the NO_2 pathway because there was no connection between exposure to such pollutant and WM scores. Besides, estimations on the removal of NO_2 by vegetation are substantial at larger scales but minimal in urban contexts, according to a study conducted in the UK (Nemitz et al., 2020) and therefore other pollutants might be better candidates to test the air pollution pathway. To our knowledge, this is the first study using ADHD as a mediator of the association between greenness/blueness and cognitive development so there is no prior evidence to compare to. Nevertheless, our results are partially supportive of the theoretical assumptions described in the DAG and presented in the current literature on residential green and blue spaces and neurodevelopment (Anabitarte et al., 2022; Dadvand et al., 2015, 2017; Reuben et al., 2019; Jimenez et al., 2021).

As mentioned in the introduction, relatively few studies have addressed the relation between residential greenness and neurodevelopment during childhood, and among those that have, the results are mixed (Anabitarte et al., 2022; Dadvand et al., 2015), this highlighting the need for further research. The data from our study contribute to this heterogeneity. First, as already stated, we found statistical support for the association between residential greenness and WM in only a small fraction of the models we were able to fit. Therefore, in general terms, our study does not offer substantial support to the hypothesis of residential greenness having a positive effect on WM. Specifically, we were unable to confirm beneficial effects of residential greenness on WM. On the other hand, this lack of supporting results could be also explained by neurodevelopmental factors. It might be that the effects of residential greenness on WM are more evident in certain periods of development and the children in our study were not in such potential windows at the times of data collection. Supporting this idea, some longitudinal studies have observed differences in the development of WM, and have described a period of latency in late childhood and an acceleration in adolescence, due to contextual and biological changes (Ahmed et al., 2022; Reynolds et al., 2022). Another possibility may lay on differential use patterns of green and blue spaces by younger and older children (Marquet et al., 2019). It may be that the detected link between NDVI and WM performance in the 6–8 years follow-up is due to longer exposure times (more frequent use of green/blue settings) or to the practice of certain activities. However, such information was not collected for this study, and we can only speculate. Finally, it is also true that our findings show effects mostly in one specific outcome, the score obtained in the 2-back number task. Performance in 3-back number tasks has been seen as an indicative of higher cognitive processing in previous studies (Dadvand et al., 2015; Fernandes et al., 2023), which may indicate that the effects of residential greenness on cognitive performance may be limited or superficial at the population level. Further studies with better characterizations of the exposure to greenness (e.g. frequency and duration of visits to parks) may help to clarify this point.

Further, it may seem intriguing that in the models for the 6- to 8-year-olds the point estimates for the (statistically significant) coefficients of the direct effects were larger in magnitude than those for the total effects. But this is only if we expect direct effects to be less than, or equal to, total effects; however, in such reasoning, we have forgotten to take into account that these estimates are, in fact, point estimates, which, naturally, have been estimated with an intrinsic error that is not reflected in the point estimate itself. Thus, when we also look at the corresponding 95% confidence intervals (which do take error into account) the supposedly intriguing result vanishes, and we observe that, when this happened, the interval estimates for direct and total effects almost completely overlap. Interval estimates are, by nature, less precise than point estimates (since interval estimates are "wider" than point estimates), but their accuracy is expressed explicitly (in this case, with 95% confidence intervals) while the accuracy of point estimates is not expressed in the estimate itself. In summary, what we may conclude when we look at these no-longer-intriguing point and interval estimates is that the size of the direct effect is of about the same magnitude as the size of the total effect; or in other words, that there is no mediation involved, i.e., that all the effect is direct since no indirect effect appears to exist despite evidence from previous studies (Aghaei et al., 2019; Alemany et al., 2018; Amoly et al., 2014; Donovan et al., 2019; Thygesen et al., 2020). For instance, in the case of taking as exposure NDVI in a 100-m buffer and as the outcome d3 colours (Table 2), the point estimate for the total effect was 0.47 with a 95% confidence interval of (−0.96, −0.02), while the point estimate for the direct effect was 0.56 with a 95% confidence interval of (−1.12, −0.01). In other words, there was no indirect effect and the observed size of the direct and total effect is negative and, with 95% accuracy, about one unit in width. The same interpretation applies to the other two cases (for NDVI in 300m and 500-m buffers as exposures and d2 numbers as the outcome).

4.1. Strengths and limitations

This study makes a meaningful contribution to the field for several reasons. First, it included three different measures of residential exposure, namely, NDVI, green space availability, and blue space availability, as well as a validated computerized task to measure WM (Forns et al., 2014). Second, the evidence here obtained adds to that provided by a small number of previous studies that describe positive effects of residential greenness on neurodevelopment scores (Anabitarte et al., 2022; Dadvand et al., 2015; Julvez et al., 2021; Reuben et al., 2019), although as in the previous research, we did not find a consistent pattern of results. Further, we had complete data for sample of children in two different age ranges that allowed us to estimate the effects of interest at two different time points. Finally, we also followed a systematic statistical procedure for selecting covariates, which involved constructing and updating a DAG (Ankan et al., 2021; Elwert, 2013; Pearl, 2000; Tennant et al., 2021; Textor et al., 2017) to select the adequate control variables and, thereby, obtain relatively unbiased estimates of the effects of residential greenness and blueness on WM. Even though the use of DAGs is becoming more common in health studies, researchers rarely test the DAG implications, which is a major methodological shortcoming (Ankan et al., 2021; Tennant et al., 2021). By so doing, we gain confidence that our estimates of the effects of interest are accurate and precise. We also trust that this procedure may consolidate within this area of research.

Nevertheless, there are some limitations. A direct consequence of focusing on the home environment is that we have not taken into account the effects of green and blue infrastructure in other potentially meaningful environments. It might be the case that the children included in the sample spent considerable amounts of time in places other than their immediate home environment (Kwan, 2009, 2012), and that green and blue features of those settings also exerted a positive effect on their WM scores. The school environment is a very clear example here (Dadvand et al., 2015). Further, although pervasive in this area of research, we have selected arbitrary boundaries (i.e., buffers) to operationalize the individual home environment which may or may not coincide with the actual area where daily activities around the home occur (Vallée et al., 2015). In their review of green space studies, Labib et al. (2020) listed a series of limitations that apply to this type of research, namely, the neglect of greenness visibility from the home, the uncertainty about the frequency and duration of use of green and blue spaces by study participants, and the quality of such spaces. These limitations might be affecting not only our ability to disentangle the total effects of greenness and bluenes on WM but also specific pathways such as the one involving the reduction of ADHD symptomatology. Including tools such as the global positioning system and accelerometry (Marquet et al., 2020), quality audits (Knobel et al., 2019), or *ad hoc* questionnaires, could help to overcome these shortcomings and gather more accurate and useful data on this matter. Our study design could not account for the role that other urban variables might play (e.g., noise) and therefore this question remains open for future studies. In addition, our study being focused on the potential mediating role of air pollution and ADHD, we did not investigate the specific role of other candidate mediators such as physical activity, temperature regulation, or noise (Buczyłowska et al., 2023; Markevych et al., 2017), although their joint effect was modelled in our direct effects models. Finally, our operationalization of SES lacked, despite comprising an individual measure (i.e., maternal education) a comprehensive area indicator, information on family income, so some residual confounding might be affecting our results.

5. Conclusion

Higher-quality neighbourhoods can promote healthier lives. This study explored the potential positive effects that residential greenness and blueness might have on WM during late childhood and early adolescence and found scarce evidence to support such a hypothesis. Despite the inconsistency of the evidence in this area of research and the fact that more work is needed to achieve a scientific consensus, our results contribute to the specific literature and warrant further examination in future studies.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2023.103136.

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