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Social inequalities, green and blue spaces and mental health in 6–12 years old children participating in the INMA cohort

Mikel Subiza-Pérez [a,b,c,d,*], Gonzalo García-Baquero [d,e], Ana Fernández-Somoano [c,f,g], Isolina Riaño [c,f,g,h], Llucia González [c,i,j], Juana Maria Delgado-Saborit [j,k], Mónica Guxens [c,l,m,n], Serena Fossati [l], Martine Vrijheid [c,l,m], Amanda Fernandes [c,l,m], Jesús Ibarluzea [c,d,o,p], Nerea Lertxundi [a,c,d]

[a] Department of Clinical and Health Psychology and Research Methods, University of the Basque Country UPV/EHU, Avenida Tolosa 70, 20018, Donostia-San Sebastián, Spain
[b] Bradford Institute for Health Research, Temple Bank House, Bradford Royal Infirmary, Duckworth Lane, BD9 6RJ, Bradford, UK
[c] Spanish Consortium for Research on Epidemiology and Public Health (CIBERESP), Instituto de Salud Carlos III, c/ Monforte de Lemos 3-5, Madrid, 280, Spain
[d] Biodonostia Health Research Institute, Group of Environmental Epidemiology and Child Development, Paseo Doctor Begiristain s/n, 20014, Donostia- San Sebastián, Spain
[e] Faculty of Pharmacy, University of Salamanca, Avda Licenciado Méndez Nieto s/n, 37007, Salamanca, Spain
[f] Unit of Molecular Cancer Epidemiology, University Institute of Oncology of the Principality of Asturias (IUOPA), Department of Medicine, University of Oviedo, Julian Clavería Street s/n, 33006, Oviedo, Asturias, Spain
[g] Instituto de Investigación Sanitaria del Principado de Asturias (ISPA), 33001, Oviedo, Spain
[h] Servicio de Pediatría, Endocrinología pediátrica, HUCA, Roma Avenue s/n. 33001, Oviedo, Asturias, Spain
[i] Faculty of Nursing and Chiropody, University of Valencia, Avda Menéndez Pelayo, 19, 46010, Valencia, Spain
[j] Joint Research Unit in Epidemiology, Environment and Health, FISABIO-University of Valencia-Universitat Jaume I, Valencia, Spain
[k] Department of Medicine, School of Health Sciences, Universitat Jaume I, Av. Vicent Sos Baynat, s/n, 12071, Castelló de la Plana, Spain
[l] ISGlobal, Barcelona, Spain
[m] Pompeu Fabra University, Barcelona, Spain
[n] Department of Child and Adolescent Psychiatry/Psychology, Erasmus MC, University Medical Centre, Rotterdam, the Netherlands
[o] Ministry of Health of the Basque Government, Sub Directorate for Public Health and Addictions of Gipuzkoa, 20013, Donostia-San Sebastián, Spain
[p] Faculty of Psychology, University of the Basque Country UPV/EHU, Avenida Tolosa 70, 20018, Donostia-San Sebastián, Spain

A R T I C L E I N F O

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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 mental health. These environmental exposures are not evenly distributed among socio-economic groups, which may increase social inequalities in mental health. The mechanisms through which natural environments may promote mental health are numerous and diverse. This study aimed to explore 1) the potential associations of socioeconomic variables (SES and maternal education attainment) with mental health scores and residential greenness, blueness and NO_2 metrics, and, 2) the association between greenness and blueness metrics and mental health scores of children in the Spanish INfancia y Medio Ambiente (INMA) birth cohort at two different time points. The study samples were composed of 1738 six-to eight-year-olds (49% female) and 1449 ten-to twelve-year-olds (living in Asturias, Gipuzkoa, Sabadell and 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. Residential NO_2 values were estimated using land use regression models. Internalizing, externalizing and total problems scores were obtained with the Strengths and Difficulties Questionnaire (SDQ). Linear and logistic mixed-effects models revealed unequal distribution of environmental exposures by SES and maternal education

* Corresponding author. Department of Clinical and Health Psychology and Research Methods, University of the Basque Country UPV/EHU, Avenida Tolosa 70, 20018, Donostia-San Sebastián, Spain.

E-mail addresses: mikel.subiza@ehu.eus (M. Subiza-Pérez), ggbmoneo@usal.es (G. García-Baquero), fernandezsana@uniovi.es (A. Fernández-Somoano), isolinariano@gmail.com (I. Riaño), gonzalez_llu@gva.es (L. González), delgado@uji.es (J.M. Delgado-Saborit), monica.guxens@isglobal.org (M. Guxens), serena.fossati@isglobal.org (S. Fossati), martine.vrijheid@isglobal.org (M. Vrijheid), amanda.fernandes@isglobal.org (A. Fernandes), mambien3-san@euskadi.eus (J. Ibarluzea), Nerea.lertxundi@ehu.eus (N. Lertxundi).

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but did not show statistically significant associations between greenness and blueness metrics and mental health indicators. The protective effect of green and blue spaces on children's mental health could not be confirmed in this study and therefore further research is required.

1. Introduction

Socioeconomic vulnerability, in the form of low income or educational attainment as well as other aspects of deprivation, increases the likelihood of poor mental health in adult (Chlapecka et al., 2020; Henking, 2022) and children (Carneiro et al., 2016) populations. Part of these social inequalities on mental health can be due to the unequal distribution of environmental factors among the population. Environmental injustice usually translates in vulnerable populations being more exposed to harmful exposures and having less access to beneficial environmental features (Murray et al., 2022). Green and blue spaces are expected to promote a stronger mental health through a wide set of potential mechanisms (Markevych et al., 2017; White et al., 2020). These include the reduction of exposure to harmful exposures such as extreme temperatures or air pollution, the promotion of salutogenic behaviours like physical activity or socialization, and, the recovery from psychological deficits including attentional fatigue, stress, anxiety or bad mood. Urban parks, green and blue infrastructure have been studied in recent years under an equity perspective (Foster et al., 2022; Hughey et al., 2016; Rigolon, 2017) and have even been proposed as a tool to reduce social inequalities on health (Mitchell et al., 2015). Social inequalities on the provision and access to blue spaces have been addressed in a small group of studies and the results are mixed (Schüle et al., 2019).

In one study conducted in the United States, SES was positively associated to residential greenness (i.e. NDVI), park coverage and availability of blue spaces (Klompmaker et al., 2023). In a similar vein, an Australian study found that neighbourhoods with higher rates of inhabitants with low income had also lower availability of green spaces (Astell-Burt et al., 2014). Median income was positively related to green space availability in Scandinavia as well (Aamodt et al., 2023). A study with a large UK population sample found that less socioeconomically affluent people visit blue settings for leisure more often than their more affluent counterparts (Elliott et al., 2018). Lower availability or access to green and blue spaces during childhood is even more critical due to their increased vulnerability to environmental factors (Landrigan et al., 2018) and one German study clearly informs about increased distance to green spaces in children of families with low income (Rehling et al., 2021).

1.1. *Predictors of internalizing and externalizing problems during childhood*

Internalizing and externalizing problems during childhood have been extensively studied as indicators of mental health and behaviour during said period of life (Goodman, 1997; Lavigne et al., 2016; Zare Sakhvidi et al., 2022). Internalizing problems refer to emotional symptoms such as psychosomatic pains or unhappiness and interactions with peers like the consideration of other people's feelings or the ability to share with others. Externalizing problems compile a diverse set of negative behaviours such as stealing or (un)following adults' requests. This latter construct also includes attention deficit and hyperactivity disorder symptoms (e.g. inability to stay still for long). Even though the pattern is not fully consistent, it can be summarized as follows. In general, children born to parents with low education and belonging to families with low socioeconomic status (SES) are more affected by internalizing and externalizing problems in said period of life (Anderson et al., 2022; Comeau and Boyle, 2018; Lansford et al., 2019; Papachristou and Flouri, 2020). Some of these works also inform about the negative relationship between maternal education and internalizing and externalizing problems (Xu et al., 2020; Zach et al., 2016). Marital status of the mother seems to have an impact on children's mental health (Comeau and Boyle, 2018; Xu et al., 2020) as well as age of the child (Ortuño-Sierra et al., 2022) and birthweight (Papachristou and Flouri, 2020). Additionally, girls and boys generally report higher internalizing and externalizing problems, respectively (Goulter et al., 2021; Ortuño-Sierra et al., 2022; Vugteveen et al., 2022; Wu et al., 2018).

Many studies have analysed the potential role of environmental exposures on children's internalizing and externalizing problems. Scores on said variables have been associated with temperature (Younan et al., 2018), neighbourhood disorder (e.g. insecurity, problematic alcohol use or vandalism, Pei et al., 2019; Ramey and Harrington, 2019) or levels of urbanicity (e.g. rural vs urban settings, Wu et al., 2018). The specific literature on residential greenness shows conflicting results. On the one hand, several works inform of a protective effect of green spaces and infrastructures on internalizing and externalizing problems (Balseviciene et al., 2014; Feng and Astell-Burt, 2017; Hartley et al., 2021; Jimenez et al., 2021). However, other works found null or mixed effects (Amoly et al., 2014; Andrusaityte et al., 2020; Flouri et al., 2014). A previous study by Bijnens and colleagues (Bijnens et al., 2020) showed protective effect of greenness on internalizing and externalizing problems only for those participants living in urban areas. These inconsistencies in the available literature are clearly reflected in a recent systematic review (Zare Sakhvidi et al., 2022) which included studies analysing the relationship between residential greenness and mental health and behaviour in children. Of the 12 associations between greenness metrics and externalizing scores, only three reached statistical significance. In the case of internalizing problems, despite most of the estimates being suggestive of protection, again only 3 out of 12 comparisons confirmed the association at the $p < 0.05$ level. When using total behavioural difficulties as outcome, only 4 out of 30 associations were statistically significant, 3 showing beneficial effects whilst the other one the opposite. Blue spaces are also expected to strengthen health, but the number of studies is reduced (Gascon et al., 2017; White et al., 2020), especially those on children's mental health (Liu and Green, 2023). With regard to blue spaces, the two studies that included such exposure identified by Green and Liu in their recent systematic review (Liu and Green, 2023) informed that annual beach attendance was inversely related to SDQ total difficulties scores (Amoly et al., 2014) and, contrary to expectations, water bodies ratio on 500m residential buffers were also negatively related to health-related quality of life in children (Tillmann et al., 2018).[1] In a study with more than 17,000 Canadians aged 11 to 16, Huynh et al. (2013) found that area of water bodies in a 5 km buffer around participants' school was not associated to well-being. Importantly, exposure during childhood to green and blue spaces seems to impact mental health not only in said period of life but also in the adulthood (Engemann et al., 2020).

Air pollution has been also linked to internalizing and externalizing problems. A study with more than 800 pre-schoolers found a positive association between prenatal NO_2 and SDQ total difficulties (Ren et al., 2019), whereas prenatal and postnatal NO_2 were associated to externalizing problems in another work (Loftus et al., 2020). A recent study conducted in China showed that exposure to NO^2 was positively related

[1] Amoly et al. (2014) operationalized annual beach attendance with two questionnaire questions in which participants' parents reported how many times a year they went with their children to the beach for leisure purposes. Water bodies ratio in Tillmann et al. (2018) study informs about the percentage of the 500 m buffer area around participants household that correspond to water bodies.

to externalizing problems (Qi et al., 2023). However, this link is not always clear (Ahmed et al., 2022; Shin et al., 2022) and more research is needed with older children.

1.3. Study aim

The objective of this study was to explore potential social inequalities on mental health and the socioeconomic distribution of residential greenness, blueness and air pollution metrics in participants in the INMA cohort study aged 6 to 8 and 10–12 years. In addition, we planned to study the effects of greenness and blueness residential exposures on mental health and to assess the mediation effects of air pollution on that association, using NO_2 levels as a surrogate of urban air pollution. We established 3 research questions:

1. Are socioeconomically vulnerable participants more affected by internalizing and externalizing problems?
2. Are residential greenness, blueness and air pollution metrics equally distributed among different socioeconomic strata?
3. Does residential greenness and blueness have a protective effect on internalizing and externalizing problems? And if so, do part of the effects of greenness and blueness effects happen through the reduction of exposure to NO_2?

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), whose mothers were recruited during the first trimester of pregnancy in health centres and hospitals of the public health system in Asturias, Gipuzkoa, Sabadell and Valencia, all different regions of Spain. These areas belong to two different climate and biogeographic regions (Dadvand et al., 2012), namely Eurosiberian (Asturias and Gipuzkoa) and Mediterranean (Sabadell and Valencia). The inclusion criteria for pregnant women in the study were being 16 years or older, having a singleton pregnancy, not having received assisted reproduction techniques, planning to give birth in the reference hospital and being able to communicate Spanish, Catalan, Basque or Valencian. Pregnancies were followed during the first and third trimester and delivery, whereas the babies have been followed-up several times since birth. In this paper, we present data from the children collected at the 6 to 8 ($n = 1738$) and 10–12 years ($n = 1449$) follow-ups. The Valencia cohort did not used SDQ at the 10–12 years follow-up so their participants were not taken into account for the 10 to 12 year-olds analyses. The ethical committees of the hospitals involved in each region approved the project and informed consent was obtained from all the participants' parents in each visit.

2.2. Study variables

2.2.1. Environmental exposures

We used two metrics of greenness to characterize participants' area of residence at each follow-up using their residential address as a reference: NDVI and availability of greenspace >5,000m.[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 (WHO Regional Office for Europe, 2016). NDVI is a measure derived from satellite imagery which was obtained for this study 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). The range of this variable is from −1 to +1 (Rugel et al., 2017), being 1 the maximum greenness level. Negative NDVI values correspond to water. Due to the fact that we aimed at getting a vegetation index for the greenest period of the year, negative NDVI values were removed before calculating the NDVI buffer averages (Peters et al., 2022; Zhang et al., 2020). We then averaged NDVI in 100m, 300m and 500m buffers around the residence address. We also included availability of major (>5,000m^2) greenspace and major (>5,000 m^2) blue space in 300m buffers using the Urban Atlas. Land covers 14100 (Green urban areas), 30000 (Forests and semi-natural areas) and 20000 (Agricultural areas) included in the Urban Atlas 2006 [2] were used to estimate this exposure for the 6–8 years follow-up. A wider set of land covers included in the Urban Atlas 2012 [3] were used for the 10–12 years follow-up: 14100 (Green urban areas), 21000 (Arable land [annual crops], 22000 (Permanent crops), 23000 (Pastures), 24000 (Complex and mixed cultivation), 25000 (Orchards), 31000 (Forests), 32000 (Herbaceous vegetation associations). Blue spaces were operationalized via the 50000 (Water) land cover in both versions of the Urban Atlas. The blue space size and the buffer radii were selected following previous studies (Binter et al., 2022; Nieuwenhuijsen et al., 2019).

2.2.2. Mediator

We calculated individual exposure to NO_2 for each follow-up through the Land Use Regression (LUR) models developed in the European Study of Cohorts for Air Pollution Effects (ESCAPE; Beelen et al., 2013). The LUR model for Asturias included surface area (m^2) of high-density residential land in a 1,000m buffer, number of households in a 5,000m 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. These LUR models were validated against the NO_2 levels obtained in intensive monitoring campaigns in each location. The variance explained (R^2) by the models was as follows: Asturias = 0.88, Gipuzkoa = 0.89, Sabadell = 0.90, and Valencia = 0.91.

2.2.3. Outcome

Participants' internalizing and externalizing problems were measured with the *Strengths and Difficulties Questionnaire* (SDQ) (Goodman, 1997). For this study we considered 20 of its items divided in 4 groups of symptoms: emotional symptoms (e.g. *often complains of headaches, stomach-aches or sickness*), conduct problems (e.g. *often has temper tantrums or hot tempers*), hyperactivity and inattention (e.g. *restless, overactive, cannot stay still for long*) and peer problems (e.g. *shares readily with other children*). In this study, parents of the participants had to indicate whether their children experienced the symptoms described in the items using a 0 *(not true)* to 2 *(certainly true)* scale. Then, emotional symptoms and peer problems are added to get an internalizing problems score and the same is done with conduct problems and hyperactivity, in order to obtain the externalizing problems one, both scores ranging from 0 to 20 points. The addition of internalizing and externalizing scores produces a total problems score on a 0–40 points range. Internal consistency of the whole instrument and the specific subscales was deemed as sufficient, with Cronbach's α indexes between 0.60 and 0.77.

[2] Copernicus. Urban Atlas. Available online: https://land.coper8nicus.eu/local/urban-atlas/urban-atlas-2006 (accessed in January 2023).

[3] Copernicus. Urban Atlas. Available online: https://land.copernicus.eu/local/urban-atlas/urban-atlas-2012 (accessed in January 2023).

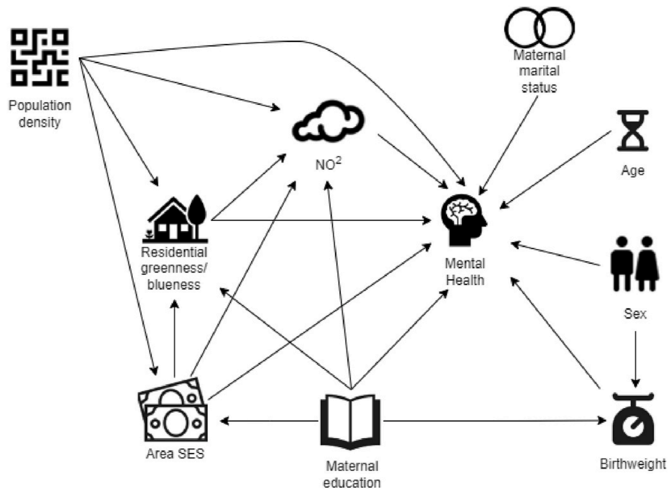

Fig. 1. DAG explaining the relationship between exposure to residential green and blue spaces and mental health (internalizing and externalizing problems). The arrows indicate causal paths. All the relationships were defined on the basis of previous literature.

2.2.3. Covariates

Based on the available literature and the available data in the cohort, a set of variables was selected as potential covariates for this study: sex of the child (female/male), age when the SDQ test was conducted, birthweight (BW, in grams), maternal marital status (stable relationship yes/no) and population density (GIS-derived measure), which we used as a proxy of urban density.[4] Maternal education (primary, secondary, university) was used as an indicator of household socioeconomic status (SES) and area-SES (1-least deprived end to 5- most deprived) was established through the index developed for the MEDEA2011 project (Domínguez-Berjón et al., 2008). This index is a composite census-tract based measure of five area indicators namely 1) unemployment 2) manual workers, 3) eventual workers, 4) insufficient education overall, and, 5) insufficient education in young people).

2.3. Data analysis

The dataset was analysed using R software v.4.0.3 (R Core Team, 2022). We began by doing descriptive statistics of the study variables and then we applied the following procedure to select control variables. First, we used the literature results described in the introduction to develop a Direct Acyclic Graph (DAG, (Pearl, 2009) that is depicted in Fig. 1. Second, we used the method described in Ankan et al. (Ankan et al., 2021) to test the DAG testable implications, which required functions included in R packages *dagitty* (Textor, 2020) and *lavaan* (Rosseel, 2012). We considered that a testable implication was unmet when its associated *r* coefficient was larger than 0.20 and had a *p*-value below the 0.05 threshold. After DAGs validation, and with the aim of further explore the relationships between study variables, we fitted Structural Equation Models (SEM) for each exposure-outcome combination in each follow-up. We then fitted regression models to analyze the effects of socio-demographic variables (i.e. maternal education, area SES) on SDQ scores and residential greenness and blueness metrics. We also fitted models to describe the total and direct effects (i.e. not including the NO_2 pathway) of residential greenness and blueness metrics on SDQ scores. For each model, we used the covariate adjustment set resulting from the updated DAG. We did so by using mixed effects modelling with the function lme() of the R package nlme (Pinheiro et al., 2022), for which we used <region> 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 to act just as sets of adjustment and hence are not interpretable. In the models where area SES was the predictor, we grouped together the 1st and 2nd quintiles to get a more numerous low-SES group. Note that the score was inverted for analyses to indicate area SES, so in the section that follows lower scores correspond to participants living in more deprived areas. In the models were NDVI was the exposure, it was expressed in IQR increases. For the models in which we tested the potential mediating role of NO_2 in the relationship between green and blue metrics and the mental health scores, we calculated the indirect effects using *medflex* (Steen et al., 2017) R package.

3. Results

Supplementary Tables 2 and 3 describe the 6 to 8 and 10 to 12 years samples. On average, they were 7.53 ($SD = 0.68$) and 11.18 ($SD = 0.69$) years old at the time when mental health was measured at each follow-up and were balanced in terms of sex (48.79% and 50.45% were female respectively). In the sample of 6 to 8 year-olds, most of mothers had completed secondary education and similar but slightly lower proportion had university education, a pattern that reversed in the sample of those aged 10 to 12 year-olds. Participants were also well distributed among SES quintiles 1 to 3 but less heavily clustered in the least affluent quintiles (4 and 5). More than four fifths of the participant's mothers were living with their partners at both times of data collection. With regard to environmental exposures, NDVI at 100 m ranged from 0.20 to 0.35 and 0.22 to 0.40 for the 6 to 8 and 10–12 years samples respectively, with greater values observed in Asturias and Gipuzkoa. A vast majority of participants lived within 300 m to a major green space in both follow-ups but only a third and a fifth of them lived near to a major blue space in the 6 to 8 and 10–12 years follow-ups respectively. NO_2 concentrations by cohort were moderate to low, with participants in Sabadell being the most exposed to such pollutant. Finally, average internalizing and externalizing problems scores were low and quite similar across the four cohorts, being the latter slightly higher than the former.

3.1. DAG validation and exploratory SEM analyses

The DAG we designed for this study comprised 25 testable implications which were met overall. Supplementary Tables 4 and 5 and Supplementary Figs. 2 and 3 show the results of this check for models using NDVI 100 m as predictor and internalizing problems score as outcome in both follow-ups. To avoid redundancy, the results of checking the testable implications for the rest of the models are not described in this paper but will be available on request. In the 6–8 years old sample, three of those were unmet; "Age ⊥ green exposure", "Age ⊥ NO2", and, "Age ⊥ population density".[5] In the 10–12 years old sample, "Area SES ⊥ Age" was unmet in all the models and "Age ⊥ Blue availability" was unmet in the models using such exposure. We updated the DAG with the relevant relations for each case and extracted the minimal set of adjustment variables for each of the models described in the following epigraphs.

As described in the data analyses section, we also conducted SEM analyses to explore the relationships between study variables. The results of such analyses are shown in Appendix 1. Also, we selected three

[4] Population density indicates the number of inhabitant per square kilometre, which was calculated with the Global Human Settlement Layer (GHSL, https://data.jrc.ec.europa.eu/dataset/jrc-ghsl-ghs_pop_gpw4_globe_r2015a). Population density values were obtained doing an intersection between population density grid maps and participants' geocodes.

[5] ⊥ 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 green exposure metrics", "age of the children is independent from their NO_2 values", and, ""age of the children is independent from their population density".

exposure-outcome combinations per follow-up and graphically showed the results of these analyses in Supplementary Tables 4 and 5.

3.2. Socioeconomic position, internalizing and externalizing problems

Table 1 shows the results of the models which aimed to assess the association between socio-economic and mental health scores in the children aged 6–8 years. There were no statistically significant associations between internalizing, externalizing or total problems scores and the SES deprivation area quintiles. However, we found that participants born to mothers with primary education showed higher internalizing, externalizing and total problems scores than those to mothers with secondary education.

As in the previous follow-up, no link between SES deprivation area quintiles and internalizing and externalizing problems could be confirmed at 10 to 12 years. Maternal education was negatively related to internalizing scores. We consistently found that children to mothers with secondary education showed lower internalizing and externalizing scores than those born to mothers with primary education.

3.3. Socioeconomic position and the distribution of greenness and air pollution metrics

Participants living in the most deprived areas at the 6 to 8 years follow-up showed lower NDVI scores than participants in the most affluent ones in all the buffers considered (100 m, 300 m and 500 m); but, surprisingly, had higher scores than those in the third quintile in the 300 and 500 m buffers (see Table 2). Participants in the third and fourth quintiles also had increased availability of green spaces than those in the lower two quintiles. Similarly, participants in the most deprived areas had lower availability of blue spaces compared to their fourth and fifth quintile counterparts. A similar pattern of results was observed for the 10 to 12 years-old participants.

NO_2 levels showed an inverted U-shape distribution, with the highest and lowest SES quintiles being associated with lower NO_2 concentrations than those in middle positions, and the third quintile showing the highest NO_2 exposure. This pattern was statistically significant for all quintiles at the 10 to 12 year-olds. On the other hand, the inverted U-shape is only suggestive in the 6–8 years follow-up since no statistically significant association is found between NO_2 exposures and deprivation index when the lowest quintile is compared with the highest. A similar inverted U-shape is suggested as regards the availability of blue spaces, with those in the fourth quintile having the greatest availability.

Maternal education was generally not associated with any of the environmental exposures considered. Children born to mothers with primary education had lower NDVI values measured in a 100 m buffer when 6–8 years of age than those born to mothers with secondary education. This association was not found in the 10 to 12 years-old sample.

Table 1
Linear mixed effects models showing the differences in mental health variables by socio-economic status and maternal educational attainment by follow-up.

Follow-up	Predictor	Outcome	Control variables	Group	Estimate	95% CI	t	p
6–8 years	SES (ref. most deprived areas: Q1+Q2)	Internalizing	urbanicity, maternal education	Q3	−0.02	(-0.30, 0.27)	−0.1	0.917
				Q4	0.04	(-0.22, 0.31)	0.32	0.747
				Q5	0.16	(-0.10, 0.41)	1.18	0.237
		Externalizing	urbanicity, maternal education	Q3	0.33	(-0.08, 0.73)	1.59	0.112
				Q4	0.10	(-0.25, 0.45)	0.56	0.573
				Q5	0.04	(-0.30, 0.38)	0.23	0.819
		Total problems	urbanicity, maternal education	Q3	0.27	(-0.30, 0.85)	0.93	0.354
				Q4	0.13	(-0.38, 0.64)	0.51	0.613
				Q5	0.21	(-0.28, 0.71)	0.84	0.34
	Maternal ed.(ref. lowest education: primary)	Internalizing	No adj.	**Secondary**	**−0.76**	**(-1.01, -0.50)**	**−5.84**	**<.001**
				University/ higher	0.09	(-0.13, 0.31)	0.80	0.425
		Externalizing	No adj.	**Secondary**	**−1.28**	**(-1.63, -0.94)**	**−7.38**	**<.001**
				University/ higher	−0.18	(-0.47, 0.11)	−1.24	0.214
		Total problems	No adj.	**Secondary**	**−2.07**	**(-2.56, -1.58)**	**−8.23**	**<.001**
				University/ higher	−0.09	(-0.51, 0.33)	−0.42	0.672
10–12 years	SES (ref. most deprived areas: Q1+Q2)	Internalizing	urbanicity, maternal education	Q3	−0.11	(-0.56, 0.33)	−0.50	0.618
				Q4	−0.11	(-0.50, 0.28)	−0.56	0.574
				Q5	0.27	(-0.13, 0.67)	1.33	0.185
		Externalizing	urbanicity, maternal education	Q3	0.44	(-0.08, 0.96)	1.66	0.098
				Q4	−0.36	(-0.82, 0.09)	−1.57	0.118
				Q5	0.01	(-0.45, 0.47)	0.04	0.965
		Total problems	urbanicity, maternal education	Q3	0.36	(0.45, 1.17)	0.88	0.381
				Q4	−0.47	(-1.17, 0.24)	−1.30	0.195
				Q5	0.29	(-0.43, 1.01)	0.78	0.437
	Maternal ed. (ref. lowest education: primary)	Internalizing	No adj.	**Secondary**	**−0.68**	**(-1.06, -0.30)**	**−3.52**	**< .001**
				University/ higher	0.24	(-0.08, 0.55)	1.49	0.137
		Externalizing	No adj.	**Secondary**	**−1.12**	**(-1.56, -0.68)**	**−4.98**	**<.001**
				University/ higher	−0.14	(-0.51, 0.22)	−0.76	0.45
		Total problems	No adj.	**Secondary**	**−1.81**	**(-2.50, 1.13)**	**−5.20**	**<.001**
				University/ higher	0.10	(-0.47, 0.67)	0.35	0.727

Note: Q refers to the inverted MEDEA index scores (1 - most deprived, 5- least deprived) and the estimates have to be interpreted as the change in the outcome as the area SES level increases.

Table 2
Linear and logistic mixed effects models showing the differences in environmental exposures by socio-economic status and maternal educational attainment by follow-up.

Follow-up	Predictor	Outcome	Control variables	Group	Estimate	95% CI	t	p
6–8 years	SES (ref. most deprived areas: Q1+Q2)	NDVI 100	urbanicity, maternal education	Q3	0	(-0.01, 0.01)	0.19	0.848
				Q4	0	(-0.01, 0.01)	0.10	0.096
				Q5	**0.01**	**(0.01, 0.02)**	**2.48**	**0.013**
		NDVI 300	urbanicity, maternal education	**Q3**	**−0.01**	**(-0.02, -0.01)**	**−2.66**	**0.007**
				Q4	0	(-0.01, 0.01)	0.52	0.605
				Q5	**0.01**	**(0.01, 0.02)**	**2.37**	**0.018**
		NDVI 500	urbanicity, maternal education	**Q3**	**−0.02**	**(-0.03, -0.01)**	**−3.13**	**0.002**
				Q4	0	(-0.01, 0.01)	1.13	0.267
				Q5	**0.01**	**(0.01, 0.02)**	**2.74**	**0.006**
		Green availability	urbanicity, maternal education	**Q3**	**0.44**	**(0.30, 0.64)**	**−4.27**	**<0.001**
				Q4	**0.56**	**(0.39, 0.81)**	**−3.13**	**0.002**
				Q5	1.15	(0.79, 1.68)	0.74	0.457
		Blue availability	urbanicity, maternal education	Q3	0.81	(0.48, 1.35)	−0.81	0.417
				Q4	**2.07**	**(1.31, 3.28)**	**3.12**	**0.002**
				Q5	**0.51**	**(0.31, 0.85)**	**−2.59**	**0.01**
		NO_2	urbanicity, maternal education	**Q3**	**2.94**	**(1.97, 3.91)**	**5.96**	**<0.001**
				Q4	**1.41**	**(0.60, 2.22)**	**3.40**	**0.001**
				Q5	−0.28	(-1.08, 0.52)	−0.69	0.488
	Maternal ed. (ref. lowest education: primary)	NDVI 100	No adj.	**Secondary**	**0.01**	**(<0.01, 0,02)**	**2.22**	**0.027**
				University/higher	−0.01	(-0.01, <0.01)	−1.34	0.181
		NDVI 300	No adj.	Secondary	0.01	(>-0.01, 0.02)	1.70	0.088
				University/higher	−0.01	(-0.01, <0.01)	−1.18	0.237
		NDVI 500	No adj.	Secondary	0.01	(-0.01, 0.01)	1.03	0.302
				University/higher	0	(-0.01, 0.01)	−0.92	0.356
		Green availability	No adj.	Secondary	0.84	(0.62, 1.15)	−1.07	0.285
				University/higher	0.86	(0.86, 0.66)	−1.04	0.297
		Blue availability	No adj.	Secondary	1.37	(0.90, 2.08)	1.47	0.141
				University/higher	1.06	(0.75, 1.49)	0.32	0.753
		NO_2	No adj.	Secondary	0.07	(-0.86, 1.02)	0.16	0.873
				University/higher	0.76	(-0.03, 1.55)	1.88	0.06
10–12 years	SES (ref. most deprived areas: Q1+Q2)	NDVI 100	urbanicity, maternal education	**Q3**	**−0.02**	**(-0.03, -0.01)**	**−2.57**	**0.01**
				Q4	0	(-0.01, 0.01)	−0.07	0.948
				Q5	**0.02**	**(0.01, 0.03)**	**0.35**	**<0.001**
		NDVI 300	urbanicity, maternal education	**Q3**	**−0.03**	**(-0.04, -0.01)**	**−4.08**	**<0.001**
				Q4	0	(-0.01, 0.01)	0.59	0.553
				Q5	**0.02**	**(0.01, 0.03)**	**3.32**	**<0.001**
		NDVI 500	urbanicity, maternal education	**Q3**	**−0.03**	**(-0.04, -0.02)**	**−4.66**	**<0.001**
				Q4	0.01	(-0.01, 0.02)	1.30	0.192
				Q5	**0.02**	**(0.01, 0.03)**	**3.37**	**0.001**
		Green avail.	urbanicity, maternal education	**Q3**	**0.43**	**(0.19, 0.49)**	**−4.27**	**<0.001**
				Q4	**0.56**	**(0.33, 0.81)**	**−3.13**	**0.002**
				Q5	1.15	(0.70, 1.81)	0.74	0.457
		Blue avail.	urbanicity, maternal education, age	Q3	0.77	(0.40, 1.48)	−0.8	0.424
				Q4	**2.80**	**(1.47, 5.34)**	**3.12**	**0.002**
				Q5	**0.36**	**(0.36, 0.76)**	**−2.68**	**0.007**
		NO_2	urbanicity, maternal education, age	**Q3**	**4.72**	**(3.62, 5.83)**	**8.40**	**<0.001**
				Q4	**1.50**	**(0.56, 2.44)**	**3.13**	**0.002**
				Q5	**−1.94**	**(-2.91, -0.97)**	**−3.94**	**0.001**
	Maternal ed. (ref. lowest education: primary)	NDVI 100	No adj.	Secondary	0.01	(-0.01, 0.02)	1.28	0.2
				University/higher	−0.01	(-0.02, 0.01)	−1.04	0.299
		NDVI 300	No adj.	Secondary	0.01	(-0.01, 0.02)	1.12	0.261
				University/higher	−0.02	(-0.02, 0.01)	−0.87	0.387
		NDVI 500	No adj.	Secondary	<0.01	(-0.01, 0.01)	0.29	0.769
				University/higher	> −0.01	(-0.02, 0.01)	−0.89	0.375
		Green avail.	No adj.	**Secondary**	**0.65**	**(0.44, 0.95)**	**−2.25**	**0.025**

(*continued on next page*)

Table 2 (*continued*)

Follow-up	Predictor	Outcome	Control variables	Group	Estimate	95% CI	t	p
				University/higher	0.97	(0.70, 1.33)	−0.22	0.829
		Blue avail.	No adj.	Secondary	1.13	(0.68, 1.88)	0.48	0.629
				University/higher	1.09	(0.73, 1.65)	0.44	0.663
		NO_2	No adj.	**Secondary**	**1.62**	**(0.52, 2.72)**	**2.89**	**0.004**
				University/higher	−0.06	(-0.96, 0.85)	−0.13	0.898

Note: Q refers to the inverted MEDEA index scores (1 - most deprived, 5- least deprived) and the estimates have to be interpreted as the change in the outcome as the area SES level increases. Models using green and blue availability as outcomes are logistic regression models.

Instead, children whose mothers had secondary education showed higher availability of green spaces and higher NO_2 concentrations than those whose mothers had primary education at 10 to 12 year-olds, which was not found at the 6–8 years follow-up.

3.4. Residential greenness and blueness, internalizing and externalizing problems

Tables 3 and 4 show the associations of residential greenness and blueness metrics with internalizing and externalizing problems scores. Most of the total and direct effects coefficients in the sample of 6–8 year-olds sample were negative, the opposite being true for the 10–12 years sample. Nevertheless, none of them reached statistical significance. Confidence intervals of total and direct effects estimates overlapped and due to the fact that both were of null statistical significance in all the models, indirect effects were not statistically significant either. Indirect effects are shown in Supplementary Tables 6 and 7.

4. Discussion

With this study we aimed to analyze the potential social inequalities on internalizing and externalizing problems, as well as the associations between socioeconomic variables and the exposure to residential greenness, blueness and air pollution in participants of the INMA cohort aged 6 to 8 and 10 to 12 years. In addition, the study aimed to evaluate whether residential greenness and blueness had a protective effect against internalizing and externalizing problems in those samples.

Contrary to previous studies (Anderson et al., 2022; Comeau and Boyle, 2018; Lansford et al., 2019; Papachristou and Flouri, 2020) no association was identified between area socioeconomic status, characterised as deprivation of the area of residence, and internalizing and externalizing problems scores for any of the samples considered. In these previous studies SES status was operationalized with self-reported income questions, however there are others using objective area-level SES data and finding statistically significant links to internalizing and externalizing problems (Martinez and Polo, 2018; Maxwell et al., 2022). It might be then that area socioeconomic vulnerability affects children mental health only in some contexts and whether this is explained by political, social, or cultural factors or simply by methodological decisions of the authors is out of the scope of this manuscript and remains open for future studies. On the other hand, maternal education was consistently associated with internalizing and externalizing problems of children, since children born to mothers with primary education showed worse scores than those born to mothers with secondary education. This was consistent with previous evidence (Comeau and Boyle, 2018; Papachristou and Flouri, 2020; Xu et al., 2020; Zach et al., 2016).

The environmental justice assumption of vulnerable people living in worse environmental quality areas (Foster et al., 2022; Murray et al., 2022; Rigolon, 2017) was only partially confirmed in our study. The pattern of results, although consistent for both follow-ups, showed social differences in the distribution of exposures by SES levels, but not always in the expected direction. Participants living in the most deprived areas were exposed to lower levels of residential greenness, according to NDVI scores, than those in the most affluent areas. However, children in the most deprived areas had higher NDVI levels than those in intermediate SES positions. Besides, children in deprived areas had higher availability of major green spaces as well. It should be highlighted that higher NDVI values, as well as increased availability of green spaces do not always mean more quality or salutogenic potential, especially in deprived areas. This was clearly shown in a review of 49 empirical studies in which the author reported that ethnic minorities and populations with low SES tended to live closer to urban parks but those are of lower acreage and quality than the green areas that other groups may use (Rigolon, 2016). Another study by the same author added that park safety is another potential factor increasing environmental inequalities (Rigolon, 2017). Nevertheless, the data gathered for

Table 3
Linear mixed total and direct effects models of residential greenness and blueness on mental health variables for the 6–8 years sample.

Exposure	Outcome	Model	Covariates	Estimate	95% CI	t	p
NDVI 100	Internalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.06	(-1.44, 1.33)	−0.08	0.934
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	0.12	(-1.37, 1.62)	0.16	0.87
NDVI 300	Internalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.01	(-1.25, 1.25)	−0.01	0.998
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	0.27	(-1.17, 1.72)	0.37	0.712
NDVI 500	Internalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.37	(-1.54, 1.72)	−0.63	0.523
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.24	(-1.66, 1.19)	−0.33	0.745
Green avail.	Internalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.20	(-0.62, 0.23)	−0.9	0.369
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.17	(-0.62, 0.28)	−0.74	0.459
Blue avail.	Internalizing	Total effects	Area SES, Age, Maternal education, urbanicity	0.22	(-0.12, 0.57)	1.27	0.204
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	0.32	(-0.06, 0.69)	1.65	0.10
NDVI 100	Externalizing	Total effects	Area SES, Age, Maternal education, urbanicity	1.21	(-0.87, 3.29)	1.14	0.256
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	1.65	(-0.55, 3.86)	1.47	0.141
NDVI 300	Externalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.73	(-2.74, 1.28)	−0.72	0.474
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.44	(-2.72, 1.83)	−0.38	0.701
NDVI 500	Externalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.96	(-2.93, 1)	−0.96	0.338
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.75	(-3.09, 1.58)	−0.63	0.528
Green avail.	Externalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.12	(-0.69, 0.46)	−0.40	0.692
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.07	(-0.66, 0.53)	−0.22	0.828
Blue avail.	Externalizing	Total effects	Area SES, Age, Maternal education, urbanicity	−0.30	(-0.90, 0.30)	−0.97	0.333
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.27	(-0.88, 0.34)	−0.88	0.378
NDVI 100	Total Problems	Total effects	Area SES, Age, Maternal education, urbanicity	0.44	(-2.48, 3.36)	0.29	0.768
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	1.22	(-1.93, 4.36)	0.76	0.448
NDVI 300	Total Problems	Total effects	Area SES, Age, Maternal education, urbanicity	−1.59	(-4.15, 0.96)	−1.23	0.22
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.95	(-4.04, 2.13)	−0.61	0.544
NDVI 500	Total Problems	Total effects	Area SES, Age, Maternal education, urbanicity	−2.14	(-4.50, 0.21)	−1.79	0.07
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−2.09	(-5.02, 0.85)	−1.39	0.164
Green avail.	Total problems	Total effects	Area SES, Age, Maternal education, urbanicity	−0.32	(-1.15, 5.10)	−0.76	0.448
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	−0.23	(-1.09, 0.64)	−0.51	0.608
Blue avail.	Total problems	Total effects	Area SES, Age, Maternal education, urbanicity	−0.06	(-0.86, 0.74)	−0.14	0.89
		Direct effects	Area SES, Age, Maternal education, urbanicity, NO_2	0.04	(-0.79, 0.86)	0.09	0.932

Table 4
Linear mixed total and direct effects models of residential greenness and blueness on mental health variables for the 10–12 years sample.

Exposure	Outcome	Model	Covariates	Estimate	95% CI	t	p
NDVI 100	Internalizing	Total effects	Area SES, Maternal education, Population density	0.14	(-0.19, 0.47)	0.85	0.397
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.12	(-0.23, 0.46)	0.68	0.505
NDVI 300	Internalizing	Total effects	Area SES, Maternal education, Population density	0.11	(-0.38, 0.61)	0.45	0.651
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.04	(-0.51, 0.59)	0.13	0.894
NDVI 500	Internalizing	Total effects	Area SES, Maternal education, Population density	0.18	(-0.38, 0.75)	0.64	0.523
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.10	(-0.58, 0.77)	0.28	0.782
Green avail.	Internalizing	Total effects	Area SES, Maternal education, Population density	0.25	(-0.29, 0.79)	0.91	0.366
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.21	(-0.36, 0.78)	0.72	0.471
Blue avail.	Internalizing	Total effects	Area SES, Maternal education, Population density, Age	0.01	(-0.57, 0.61)	0.07	0.944
		Direct effects	Area SES, Maternal education, Population density, Age, NO_2	−0.01	(-0.60, 0.59)	−0.01	0.992
NDVI 100	Externalizing	Total effects	Area SES, Maternal education, Population density	0.18	(-0.20, 0.57)	0.93	0.355
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.22	(-0.17, 0.62)	1.12	0.264
NDVI 300	Externalizing	Total effects	Area SES, Maternal education, Population density	0.01	(-0.57, 0.58)	0.02	0.981
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.10	(-0.54, 0.73)	0.30	0.764
NDVI 500	Externalizing	Total effects	Area SES, Maternal education, Population density	−0.08	(-0.74, 0.59)	−0.22	0.823
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.04	(-0.75, 0.82)	0.09	0.927
Green avail.	Externalizing	Total effects	Area SES, Maternal education, Population density	0.19	(-0.44, 0.82)	0.59	0.553
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.26	(-0.39, 0.92)	0.79	0.43
Blue avail.	Externalizing	Total effects	Area SES, Maternal education, Population density, Age	−0.06	(-0.76, 0.65)	−0.16	0.876
		Direct effects	Area SES, Maternal education, Population density, Age, NO_2	−0.05	(-0.76, 0.66)	−0.15	0.889
NDVI 100	Total Problems	Total effects	Area SES, Maternal education, Population density	0.31	(-0.28, 0.91)	1.03	0.303
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.33	(-0.29, 0.94)	1.04	0.298
NDVI 300	Total Problems	Total effects	Area SES, Maternal education, Population density	0.11	(-0.79, 1.01)	0.25	0.805
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.12	(-0.87, 1.11)	0.23	0.817
NDVI 500	Total Problems	Total effects	Area SES, Maternal education, Population density	0.10	(-0.94, 1)	0.19	0.851
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.10	(-1.12, 1.33)	0.17	0.868
Green avail.	Total problems	Total effects	Area SES, Maternal education, Population density	0.45	(-0.53, 1.42)	0.90	0.369
		Direct effects	Area SES, Maternal education, Population density, NO_2	0.47	(-0.54, 1.49)	0.91	0.362
Blue avail.	Total problems	Total effects	Area SES, Maternal education, Population density, Age	−0.01	(-1.07, 1.04)	−0.02	0.984
		Direct effects	Area SES, Maternal education, Population density, Age, NO_2	−0.01	(-1.08, 1.05)	−0.02	0.983

this study does not allow testing for potential inequalities in park quality and safety.

Availability of major blue spaces also differed by SES and the analyses of NO_2 levels interestingly revealed that participants residing in the most and least deprived areas were less exposed to those environmental factors than their mid-SES counterparts. In a whole, these results are consistent with the finding that social patterns of environmental exposures are diverse in Europe and not always align with environmental injustice hypotheses as it was shown elsewhere (European Environment Agency, 2022; Robinson et al., 2018). This might indicate that, despite being a powerful concept to understand urban exposures globally, studies specific to each location are to be carried out in order to detect which groups are more and less exposed to which environmental exposures and tailor distinct interventions accordingly.

Finally, our results did not support the expected protective effects of green and blue spaces on internalizing and externalizing problems (Markevych et al., 2017; White et al., 2020). These results are nevertheless consistent with the outcomes of a recent literature review where most studies show null effects (Zare Sakhvidi et al., 2022). According to that review, only a 25% of the associations between residential greenness and either internalizing or externalizing problems were statistically significant and therefore our results are consistent with previous literature. The absence of a consistent and incontrovertible body of evidence on these matters might be due to either methodological deficiencies in epidemiological research (see epigraph below) or the fact that said benefits are only apparent in certain populations or groups. The conduction on more studies with more robust designs will help to elucidate this issue and establish guidelines and recommendations to future interventions.

4.1. Study 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 scale to measure internalizing and externalizing problems (Goodman, 1997). Second, the evidence here obtained adds to that provided by previous studies in three main literature bodies, the ones on social inequalities on mental health, environmental justice and greenness and mental health. The sample size of the study is considerable and we could estimate the effects of interest at two different time points. Last but not least, we selected the covariates for the statistical models through a process which began with the identification of potential covariates, followed by the construction and validation of a DAG (Elwert, 2013; Pearl, 2000; Tennant et al., 2021; Textor et al., 2017) and concluded with the estimation of unbiased associations via covariate adjustment. The use of DAGs is becoming more and more popular in health studies but the testable Implications are rarely checked, which constitutes a major methodological shortcoming (Ankan et al., 2021; Tennant et al., 2021). This way, we increased the accuracy and precision of our estimates and advanced the consolidation of such procedure in this area of research.

Nevertheless, there are some limitations that must be considered when extracting conclusions from our study. We have focused only on the residential environment and therefore ignored other potentially important environments such as school or leisure settings (Kwan, 2009, 2012. Following previous studies, we 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 addition, our study design did not consider relevant contextual variables as the quality of green and blue spaces, the frequency and duration of participants visits to those, if any, or the safety of these spaces. These are common deficits in environmental studies on greenness and health (Labib et al., 2020) that should be addressed by means of global positioning system and accelerometry devices (Marquet et al., 2020), park quality audits (Knobel et al., 2019) and specific questionnaires (McEachan et al., 2018). These limitations, which negatively affect to our capacity to characterize exposure to green and blue spaces, might be indeed responsible for the mixed and inconsistent pattern of results observed in the literature. The suggestions made above (e.g. use of GPS devices) could contribute to obtain better quality evidence. Such evidence will be helpful to define if green space prescriptions are universally beneficial or, in the contrary, if there are certain population groups that are not accessing those benefits and whether specific interventions should be implemented.

5. Conclusion

One of the main social responsibilities of environmental epidemiology is to map the health implications that environmental exposures may entail for the general population, understand their explanatory mechanisms and tailor effective interventions. Greenness and blueness are currently receiving a considerable attention by environmental epidemiologists but the empirical results do not always align with their theoretical expectations. This study contributes to the specific literature by adding new evidence which can help to define the map of environmental exposures (un)affecting children's mental health.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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