



The association between greenness and traffic-related air pollution at schools



Payam Dadvand^{a,b,c,*}, Ioar Rivas^{a,b,c,d}, Xavier Basagaña^{a,b,c}, Mar Alvarez-Pedrerol^{a,b,c}, Jason Su^e, Montserrat De Castro Pascual^{a,b,c}, Fulvio Amato^d, Michael Jerret^e, Xavier Querol^d, Jordi Sunyer^{a,b,c}, Mark J. Nieuwenhuijsen^{a,b,c}

^a Centre for Research in Environmental Epidemiology (CREAL), C/Dr. Aiguader 88, 08003 Barcelona, Spain

^b CIBER Epidemiología y Salud Pública (CIBERESP), C/Monforte de Lemos 3-5, 28029 Madrid, Spain

^c Universitat Pompeu Fabra (UPF), Plaça de la Mercè, 08002 Barcelona, Spain

^d Institute of Environmental Assessment and Water Research (IDAEA), Spanish National Research Council (CSIC), C/Jordi Girona 18-26, 08034 Barcelona, Spain

^e Environmental Health Sciences, School of Public Health, University of California, Berkeley, 50 University Hall, Berkeley, CA, 94720-7360, USA

HIGHLIGHTS

- Reduced indoor and outdoor air pollution associated with greenness within schools.
- Reduced indoor and outdoor air pollution associated with greenness around schools.
- Reduction in indoor air pollution was mediated by reduction in outdoor levels.

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ABSTRACT

Greenness has been reported to improve mental and physical health. Reduction in exposure to air pollution has been suggested to underlie the health benefits of greenness; however, the available evidence on the mitigating effect of greenness on air pollution remains limited and inconsistent. We investigated the association between greenness within and surrounding school boundaries and monitored indoor and outdoor levels of traffic-related air pollutants (TRAPs) including NO₂, ultrafine particles, black carbon, and traffic-related PM_{2.5} at 39 schools across Barcelona, Spain, in 2012. TRAP levels at schools were measured twice during two one-week campaigns separated by 6 months. Greenness within and surrounding school boundaries was measured as the average of satellite-derived normalized difference vegetation index (NDVI) within boundaries of school and a 50 m buffer around the school, respectively. Mixed effects models were used to quantify the associations between school greenness and TRAP levels, adjusted for relevant covariates. Higher greenness within and surrounding school boundaries was consistently associated with lower indoor and outdoor TRAP levels. Reduction in indoor TRAP levels was partly mediated by the reduction in outdoor TRAP levels. We also observed some suggestions for stronger associations between school surrounding greenness and outdoor TRAP levels for schools with higher number of trees around them. Our observed reduction of TRAP levels at schools associated with school greenness can be of public importance, considering the burden of health effects of exposure to TRAPs in schoolchildren.

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1. Introduction

Contact with greenness has been shown to improve perceived and objective physical and mental health (Bowler et al., 2010; Lee and Maheswaran, 2011). Although the underlying mechanisms of health benefits of greenness are not well understood, reduction in exposure to air pollution has been suggested as one explanation (Bowler et al., 2010). The available evidence, however, on the mitigating effect of greenness on air pollution with regard to human exposure remains limited and inconsistent (Dadvand et al., 2012a, Hagler et al., 2012).

Abbreviations: BC, black carbon; BREATHE, BRain dEvelopment and Air polluTion ultra-fine particles in scHool children; CI, confidence intervals; IQR, interquartile range; NDVI, normalized difference vegetation index; LDSA, lung-deposited surface area; LUR, land use regression; PM_{2.5}, particulate matter with aerodynamic diameter ≤ 2.5 μm; RC, regression coefficient; TRAP, traffic-related air pollutant; UFP, ultrafine particles; VOC, volatile organic compound.

* Corresponding author at: CREAL, Doctor Aiguader, 88, 08003 Barcelona, Spain.

E-mail address: pdadvand@creal.cat (P. Dadvand).

Children spend a large proportion of their time at school when traffic pollution peaks during the day. Many schools are located in proximity to busy roads, increasing the level of traffic-related air pollutants (TRAPs) at the schools. Exposure to TRAPs at school has been associated with a range of adverse health impacts including respiratory conditions (McConnell et al., 2010) and impaired neurodevelopment (Shu et al., 2009) in schoolchildren, which are accompanied with a considerable personal and societal burden.

This study aimed to investigate the association between school greenness (separately for greenness within boundaries of schools and greenness surrounding schools) and TRAP levels at schools (separately for indoor and outdoor levels).

2. Methods

We undertook this study in Barcelona, Spain, a port city situated on the Northeastern part of the Iberian Peninsula. Air pollution concentrations in Barcelona are among the highest in Europe. It has a Mediterranean climate characterized by hot and dry summers, mild winters, and maximum precipitation and vegetation during autumn and spring. This study was conducted in the context of the BRain dEvelopment and Air polluTion ultrafine particles in sChool childrEn (BREATHE) project (Amoly et al., 2014).

2.1. Schools

Of the 416 schools in Barcelona, 37 schools were initially selected to obtain maximum contrast in TRAP levels (i.e., NO_2); 36 (18 pairs) agreed to participate and were included in the study. Low and high NO_2 schools were paired by neighborhood socioeconomic status and type of school (public vs. private). Additionally, three more schools from an adjacent municipality, Sant Cugat del Vallès, were included in BREATHE (39 schools in total). Participating schools were similar to the remaining schools in Barcelona in terms of the socioeconomic vulnerability index (0.46 versus 0.50, $p = 0.57$) and NO_2 levels (51.5 versus $50.9 \mu\text{g}/\text{m}^3$, $p = 0.72$).

2.2. Air pollution measurements

We selected NO_2 , black carbon (BC), and ultrafine particles (UFPs) given their relation to road traffic emissions in Barcelona (Amato et al., 2014; Reche et al., 2014; Rivas et al., 2014). For UFP (in the range of 10–700 nm), we separately analyzed number concentration and lung-deposited surface area (UFP-LDSA). Because of the strong correlation between these two variables (Spearman's correlation coefficient of 0.9) and consistency of the findings for them, for this short communication we only present the results for UFP-LDSA, which is likely to be more biologically relevant.

TRAP levels at each pair of schools were simultaneously measured twice during one-week campaigns separated by 6 months, once in the warm and once in the cold seasons of the year 2012. The sampling was simultaneously performed indoors (in a classroom) and outdoors (in the playground). Air samples were collected at a height between 0.7 and 1.5 m above floor level, which is the height at which the pupils aged 7–9 would usually inhale. Real-time BC and UFP concentrations were measured using MicroAeth AE51 (AethLabs, USA) and DiSCmini (Matter Aerosol, Switzerland) monitors, respectively, during the 8-hour school time when children were at school. The DiSCmini device is based on unipolar charging of the particle, followed by their detection in two electrometer stages. The charge is size-dependent, and the LDSA is proportional to the diffusion charger signal. This method has been detailed in (Fierz et al., 2011). Weekly averaged NO_2 concentrations were measured by Gradko Environmental passive dosimeters. Detailed description of sampling methodology has been previously published (Amato et al., 2014; Reche et al., 2014; Rivas et al., 2014).

Furthermore, based on chemical analysis of the 8-hour a day particulate matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$ ($\text{PM}_{2.5}$) samples collected by high volume ($30 \text{ m}^3/\text{h}$) MCV samplers, we estimated the contribution of traffic to $\text{PM}_{2.5}$ concentrations using a Positive Matrix Factorization model as described elsewhere (Amato et al., 2014). This traffic-related $\text{PM}_{2.5}$ concentration (hereafter referred to as $\text{PM}_{2.5}$ -traffic) comprised organic particles from motor exhaust, elemental carbon as well as metals from brake wear (Cu, Sb, Sn and Fe). We used $\text{PM}_{2.5}$ -traffic as another indicator of TRAP at schools.

2.3. School greenness

We assessed the greenness within and around the school boundaries by means of normalized difference vegetation index (NDVI) (Weier and Herring, 2011) derived from RapidEye images at $5 \text{ m} \times 5 \text{ m}$ resolution. The RapidEye imagery is acquired from a constellation of five satellites 630 km above ground in sun-synchronous orbits. Each satellite has a multi-spectral push broom imager sensor that collects data in blue, green, red, red edge and near-infrared. NDVI is an indicator of greenness based on land surface reflectance of visible (red) and near-infrared parts of spectrum (Weier and Herring, 2011). It ranges between -1 and 1 with higher numbers indicating more greenness. We generated our NDVI map using the image obtained on July 23rd, 2012. This image was radiometrically corrected and presented in pixel values (digital numbers). These digital numbers were converted to the Top of Atmosphere radiance before the NDVI was estimated.

To assess greenness within school premises we first digitized the school boundaries and then averaged NDVI values within those boundaries. To assess greenness surrounding schools we averaged NDVI values in a 50 m buffer around the school boundaries.

2.4. Statistical analysis

For each exposure–outcome pair, we developed mixed effects models with school as random effect to account for the repetitive measurements for each school. We used weekly indoor and outdoor levels of each TRAP (one at a time) measured during each campaign as the outcome and greenness within and surrounding school boundaries (one at a time) as fixed-effect predictors. Given that different school pairs were monitored in different weeks during each campaign period, we adjusted the analyses of each TRAP for the weekly average level of that TRAP (during the corresponding sampling week for each school pair) measured by a background monitoring station in Barcelona to remove temporal fluctuation in background TRAP levels from our analyses (Rivas et al., 2014). We further adjusted the models of indoor TRAPs for meteorological indicators (average temperature and humidity and total precipitation during the sampling week), monitor placement (ground floor: yes/no) and orientation (facing inward/towards street/towards playground), and school characteristics including building age and ventilation as fixed-effect predictors. Air-conditioning systems or heaters were not available in any of the classrooms and natural ventilation through windows and doors was the only type of ventilation in classrooms. Teachers were asked to fill in a logbook describing the frequency with which the windows and doors were opened during the sampling period.

In addition to background TRAP levels, models of outdoor TRAPs were adjusted for meteorological indicators and monitor placement as fixed-effect predictors. To address the impact of traffic around the school, we further adjusted the analyses of outdoor TRAPs for those traffic indicators that showed to be the best predictors for each TRAP in land use regression (LUR) models developed for Barcelona (Beelen et al., 2013; Eeftens et al., 2012). Accordingly, the analyses for outdoor NO_2 levels were further adjusted for squared distance to the nearest major road, product of traffic intensity on the nearest road and inverse of distance to the nearest road, and total length of roads (all types) in a 1000 m buffer around the school. For $\text{PM}_{2.5}$ -traffic and UFP there was

Table 1
Spearman's correlation coefficient between TRAP levels.

	NO ₂	UPF (LDSA)	Black carbon	Traffic-related PM _{2.5}
Indoor levels				
NO ₂	1			
UPF (LDSA)	0.64	1		
Black carbon	0.65	0.88	1	
Traffic-related PM _{2.5}	0.64	0.80	0.87	1
Outdoor levels				
NO ₂	1			
UPF (LDSA)	0.69	1		
Black carbon	0.68	0.85	1	
Traffic-related PM _{2.5}	0.65	0.76	0.81	1

no LUR model available and we adjusted the analyses for the same traffic predictors as BC including total traffic load (all road types) within 50 m around the school boundaries and the product of traffic intensity on the nearest road and inverse of distance to the nearest road. StataCorp Stata statistical software (Release 12) was used to carry out the analyses.

3. Results

We successfully obtained 77 weekly samples for the analyses; one school had only one sampling campaign conducted. The median (interquartile range (IQR)) of greenness within and surrounding school boundaries was 0.106 (0.087) and 0.110 (0.144), respectively. The Spearman's correlation coefficient between greenness within and surrounding school boundaries was 0.74. The Spearman's correlation

coefficient between TRAP levels is presented in Table 1. The median (IQR) of pollutant levels is presented in Table 2.

As presented in Table 2, higher greenness within and surrounding school boundaries was consistently associated with lower indoor and outdoor TRAP levels. The findings for UFP number concentration were similar to those of UFP-LDSA. Using buffers of 25 m and 100 m (instead of 50 m buffer) to abstract school surrounding greenness did not result in a notable change in the aforementioned associations. Further adjustment of outdoor NO₂ for more traffic indicators including total traffic load in 50 m and 100 m buffer around the school and total traffic load in major roads in a 50 m buffer around school (one at a time) did not result in a notable change in our findings. Similarly, further adjustment of analyses of outdoor BC, UFP-LDSA, and PM_{2.5}-traffic for squared distance to the nearest major road, total traffic load in major roads in a 50 m buffer around school, and total length of roads (all types) in a 1000 m buffer around the school did not change the findings notably. After including a 15-minute traffic count in the closest street to the school (counted by a technician during the second air sampling campaign in each school) in models for outdoor TRAP levels (instead of total traffic load in a 50 m buffer around the school) the association between traffic-related PM_{2.5} and greenness within school boundaries became marginally non-significant: -0.7 (-1.8, 0.3) (Appendix Table A1), while for the rest of the associations, the interpretation of the results stayed unchanged. Moreover, further adjustment of analyses of indoor TRAP levels for corresponding traffic indicators for each TRAP indicators did not alter our findings notably with the exception of our observed association between indoor NO₂ levels and greenness within school which became weaker and lost its statistical significance (regression coefficient = -2.5 and 95% confidence intervals (CI) = -6.3, 1.4).

We adjusted our analyses for both background TRAP levels and meteorological indicators that might have resulted in over-adjustment

Table 2
Median (interquartile range (IQR)) of pollutant levels and regression coefficients (RC) and 95% confidence intervals (CI) indicating the change in air pollutant levels associated with one IQR^a increase in average of NDVI within and surrounding (50 m buffer) the school boundaries.

	Median level (IQR)	Within school		Surrounding school	
		RC (95% CI)	p	RC (95% CI)	p
Indoor					
NO ₂ (µg·m ⁻³)	30.0 (16.8)				
Unadjusted		-6.4 (-10.8, -2.0)	<0.01	-12.6 (-16.5, -8.7)	<0.01
Adjusted ^b		-4.2 (-8.0, -0.3)	0.04	-9.8 (-13.5, -6.0)	<0.01
UPF (LDSA) (µm ² ·cm ⁻³)	31.2 (19.0)				
Unadjusted		-8.2 (-12.4, -4.1)	<0.01	-12.0 (-16.4, -7.7)	<0.01
Adjusted ^b		-7.3 (-11.0, -3.6)	<0.01	-11.5 (-15.2, -7.7)	<0.01
Black carbon (µg·m ⁻³)	1.2 (0.7)				
Unadjusted		-0.36 (-0.52, -0.19)	<0.01	-0.49 (-0.66, -0.32)	<0.01
Adjusted ^b		-0.29 (-0.40, -0.17)	<0.01	-0.37 (-0.50, -0.24)	<0.01
Traffic-related PM _{2.5} (µg·m ⁻³)	4.5 (4.1)				
Unadjusted		-1.9 (-2.9, -1.0)	<0.01	-2.9 (-3.9, -2.0)	<0.01
Adjusted ^b		-1.5 (-2.4, -0.7)	<0.01	-2.7 (-3.6, -1.8)	<0.01
Outdoor					
NO ₂ (µg·m ⁻³)	46.2 (19.7)				
Unadjusted		-7.3 (-12.9, -1.8)	0.01	-13.7 (-19.2, -8.1)	<0.01
Adjusted ^c		-4.4 (-8.1, -0.8)	0.02	-9.8 (-14.8, -4.9)	<0.01
UPF (LDSA) (µm ² ·cm ⁻³)	40.3 (17.5)				
Unadjusted		-8.1 (-13.6, -2.6)	<0.01	-13.9 (-19.4, -8.4)	<0.01
Adjusted ^d		-9.0 (-13.8, -4.1)	<0.01	-14.6 (-19.4, -9.8)	<0.01
Black carbon (µg·m ⁻³)	1.2 (0.8)				
Unadjusted		-0.27 (-0.45, -0.08)	<0.01	-0.47 (-0.65, -0.28)	<0.01
Adjusted ^d		-0.30 (-0.44, -0.16)	<0.01	-0.46 (-0.60, -0.32)	<0.01
Traffic-related PM _{2.5} (µg·m ⁻³)	5.0 (4.8)				
Unadjusted		-1.2 (-2.3, 0.0)	0.05	-2.4 (-3.6, -1.2)	<0.01
Adjusted ^d		-1.5 (-2.5, -0.4)	<0.01	-2.7 (-3.9, -1.6)	<0.01

^a 0.087 and 0.144 for greenness within and surrounding school boundaries respectively.

^b Adjusted for weekly average of background level of that pollutant, meteorological indicators (temperature, humidity, and precipitation), monitor placement (floor and orientation), and school characteristics including building age and ventilation.

^c Adjusted for weekly average of background level of that pollutant, meteorological indicators (temperature, humidity, and precipitation), monitor placement (floor and orientation), and traffic indicators (squared distance to the nearest major road, product of traffic intensity on the nearest road and inverse of distance to the nearest road, and total length of roads (all types) in a 1000 m buffer around the school).

^d Adjusted for weekly average of background level of that pollutant, meteorological indicators (temperature, humidity, and precipitation), monitor placement (floor and orientation), and traffic indicators (the product of traffic intensity on the nearest road and inverse of distance to the nearest road and total traffic load (all road types) in a 50 m buffer around the school).

given the correlation of meteorological factors and background TRAP levels. After meteorological indicators were removed from the analyses, for indoor TRAP levels the estimated associations became generally weaker and for indoor NO₂ levels lost its statistical significance; whereas for outdoor TRAP levels the estimated associations became stronger. These findings might suggest that for indoor TRAP analyses, the meteorological indicators were possibly surrogating the ventilation rate of classroom while for outdoor TRAP analyses, and inclusion of these indicators could have resulted in over-adjustment of models.

School area was associated with outdoor UFP-LDSA levels ($p = 0.02$) but was not associated with the rest of the pollutants (all p -values > 0.10). After we adjusted the analyses of outdoor UFP-LDSA for the school area, the association for greenness within school boundaries attenuated and became nearly significant (regression coefficient = -5.8 and 95% CI: $-12.0, 0.4$; $p = 0.067$), while for the greenness surrounding school boundaries, it didn't change notably and remained statistically significant (regression coefficient = -13.1 and 95% CI: $-19.1, -7.2$; $p < 0.001$).

4. Discussion

To our knowledge, this short communication is the first available report on the effect of greenness on TRAP levels at schools which also adds to the limited available body of evidence on mitigating effect of greenness on air pollution. We found that higher greenness within and surrounding school boundaries was associated with lower indoor and outdoor TRAP levels.

The observed inverse association between school greenness and TRAP is consistent with findings of our previous study showing that higher residential surrounding greenness was associated with reduced personal and home-indoor and home-outdoor PM_{2.5} levels in Barcelona (Dadvand et al., 2012a). Our findings are also in line with available literature on LUR models reporting that including greenness as a predictor in LUR models can improve their predictive efficacy for TRAPs (Su et al., 2009).

Because of high correlation between greenness within and surrounding school boundaries, it was not possible to determine the independent impact of one or the other. We generally observed stronger associations for greenness surrounding the school boundaries than greenness within school boundaries, which might suggest that part of our observed associations could be explained by lower traffic in greener areas (open space effect). The moderately high negative correlation between traffic and greenness within a 50 m buffer around the school and traffic within a 50 m buffer around the school (Spearman's correlation coefficient of -0.66) and total length of roads (all types) in a 1000 m buffer around the school (Spearman's correlation coefficient of -0.57) supports this interpretation. Greenness, however, has been proposed to reduce air pollution by direct and indirect mechanisms (Givoni, 1991). The direct mechanism is through the filtering effect of plants, principally based on dry deposition of pollutants (both particles and gases) through stomata uptake or non-stomata deposition on plant surfaces (Akbari, 2002; Givoni, 1991; Nowak et al., 2006; Paoletti et al.), although this effect is likely to be modest on a local scale. The indirect effect is mediated by improving urban ventilation, which in turn increases the dispersal of the pollutants (Givoni, 1991). While our study was dealing with greenness within and surrounding school boundaries, a majority of the available evidence on the mitigating effect of vegetation on air pollution has focused on such an effect for roadside vegetation showing inconsistent results with some reports that do not support such an effect (Baldauf et al., 2011; Hagler et al., 2012). Simulation studies have also suggested that roadside trees can generate a canyon effect with higher TRAP levels on the downwind and lower TRAP levels on the upwind side of the street (Baldauf et al., 2011; Buccolieri et al., 2009). Furthermore, vegetation produces volatile organic compounds (VOCs) that can engage in complex photo-chemical reactions with other air pollutants like ozone and NO_x and can participate in the

generation of biogenic secondary organic aerosols (Hoyle et al., 2011; Kesselmeier and Staudt, 1999). Such effects were out of the scope of this short communication dealing with TRAPs and remain as open questions for future studies.

We included indoor TRAP levels in our study because children spend most of their school time in classrooms and consequently the classroom TRAP levels can be a major determinant of TRAP exposure for schoolchildren. We hypothesized that our observed inverse associations between school greenness and indoor TRAP levels could have been, at least in part, mediated by reduction in outdoor TRAP levels associated with school greenness. To explore such mediation, we included outdoor levels of each TRAP in the fully adjusted models for indoor levels of that TRAP (e.g., for the analysis of the association between indoor NO₂ levels and school greenness, we further adjusted the models for outdoor NO₂ levels). After such inclusion, the inverse associations between greenness and indoor TRAP levels became much weaker (Appendix Table A2) suggesting that these associations could be explained partly by our observed reduction in outdoor TRAP levels associated with higher greenness.

Our study used remote sensing-derived NDVI to measure surrounding greenness. Application of this objective measure of greenness enabled our study to take account of small green spaces (e.g., home gardens, street trees and green verges) in a standardized way; however, NDVI does not distinguish between different types of vegetation. This distinction may be important because there is some evidence that the effect of green spaces on air pollutants is vegetation-dependent (Givoni, 1991). To better characterize the vegetation type, we abstracted *school surrounding tree count* as the number of trees within 50 m around the school boundaries for a subset of 31 BREATHE schools that were covered by an available map of trees in Barcelona. This map has been generated by the Barcelona City Council (2013) and details the location and species of each single tree that is maintained by the city. The Spearman's correlation coefficient between the number of trees and the average of NDVI within 50 m around the school boundaries was 0.54. After repeating the main analyses for outdoor TRAP levels by using school surrounding tree count instead of indicators of school greenness in fully adjusted models, we observed consistent findings with the main analyses in terms of direction and statistical significance of the associations, with the exception of traffic-related PM_{2.5} for which the association was no longer statistically significant (Appendix Table A3). To explore how tree composition of school surrounding greenness

Table 3

Adjusted regression coefficients (RC) and 95% confidence intervals (CI) indicating the change in air pollutant levels associated with one IQR^a increase in average of NDVI surrounding (50 m buffer) the school boundaries separately for schools with surrounding tree counts lower and higher than median school surrounding tree counts (91 trees).

Outdoor levels	School surrounding greenness (average NDVI)			
	Lower tree count		Higher tree count	
	RC (95% CI)	p	RC (95% CI)	p
NO ₂ ^b	-2.7 (-7.9, 2.5)	0.303	-5.2 (-10.3, -0.1)	0.047
UFP (LDSA) ^c	-6.7 (-12.1, -1.2)	0.016	-10.0 (-17.4, -2.6)	0.008
Black carbon ^c	-0.17 (-0.39, -0.04)	0.011	-0.35 (-0.60, -0.11)	0.004
Traffic-related PM _{2.5} ^c	-0.7 (-1.6, 0.2)	0.108	-2.3 (-4.0, -0.6)	0.009

^a 0.060 and 0.102 for lower and higher tree content schools respectively.

^b Adjusted for weekly average of background level of that pollutant, meteorological indicators (temperature, humidity, and precipitation), monitor placement (floor and orientation), and traffic indicators (squared distance to the nearest major road, product of traffic intensity on the nearest road and inverse of distance to the nearest road, and total length of roads (all types) in a 1000 m buffer around the school).

^c Adjusted for weekly average of background level of that pollutant, meteorological indicators (temperature, humidity, and precipitation), monitor placement (floor and orientation), and traffic indicators (the product of traffic intensity on the nearest road and inverse of distance to the nearest road and total traffic load (all road types) in a 50 m buffer around the school).

could have affected our findings for outdoor TRAP levels, we divided and stratified the main analyses for outdoor TRAP levels according to the median of school surrounding tree count (91 trees) to compare the associations for schools with the higher tree content (i.e., tree counts more than median) and lower tree content (i.e., tree counts less than median). As presented in Table 3, the associations between outdoor TRAP levels and greenness (i.e., average NDVI) surrounding school boundaries were stronger for schools with higher surrounding tree count compared with those with lower counts, which is consistent with available literature reporting that trees are the most effective vegetation type in mitigating air pollution levels (Givoni, 1991).

By using the NDVI map obtained at a single point of time, we effectively assumed that the spatial distribution of NDVI across our study region remained constant over the study period. The findings of our previous studies support the stability of the NDVI spatial contrast over seasons and years (Dadvand et al., 2012b, 2014).

5. Conclusions

We found an inverse association between greenness within and surrounding school boundaries and indoor and outdoor TRAP levels at schools. There were some indications that the reduction in indoor TRAP levels could have been partly mediated by the reduction in outdoor TRAP levels associated with higher school greenness. We also observed some suggestions for stronger associations between school surrounding greenness and outdoor TRAP levels for schools with higher number of trees around them. Considering the high burden of health effects of TRAP exposure on schoolchildren, if our findings are confirmed by future studies, they might inform policymakers and health professionals about the importance of school and neighborhood greenness to avoid such burdens and at the same time to achieve other health co-benefits of greenness such as better behavioral development (Amoly et al., 2014) and school performance (Wu et al., 2014). Future studies could usefully include vegetation type and include other air pollutants such as ozone and VOCs in their analyses.

Conflict of interest

The authors declare that they do not have any actual or potential financial and personal conflict of interest with other people or organizations.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.scitotenv.2015.03.103>.

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