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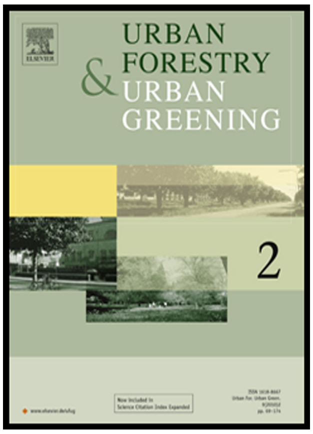

Greenness around Brazilian schools may improve students' math performance but not science performance

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Greenness around Brazilian schools may improve students' math performance but not science performance

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Abstract

Green spaces play a vital role in the social, economic, and physical well-being of people. To further research on this topic, in this paper, we estimated the association of greenness and academic performance at the school-level in Brazil. We analyzed this association using mixed-effects regression models, adjusted for air pollution, SES, and spatiotemporal terms. We used the Normalized Difference Vegetation Index (NDVI) as the exposure variable. Data from the high school national exam in Brazil (at the school level, measured with a score varying from 0 to 1,000) was used to represent the academic performance. The primary analysis results indicate that green areas surrounding schools are positively associated with school-level academic performance in math, with an estimated coefficient of 17.18 (95%CI: 10.46; 23.90). The results were statistically insignificant for science, with a coefficient of -2.39 (95%CI: -7.49; 2.71). Our findings are relevant for policymakers and urban planners to improve the environment surrounding schools to promote public health by making schools healthier.

Keywords

Greenness, Normalized Difference Vegetation Index (NDVI), Students, Academic performance

1. INTRODUCTION

Environmental exposure surrounding schools has been considered a crucial public health concern (Hodson and Sander, 2017). The built environment, socioeconomic conditions, and environmental factors of neighborhoods are potential predictive variables to estimate the risk of morbidity and mortality (Baldauf et al., 2013; Requia et al., 2016; Wilker et al., 2013). Studies have shown that the aspects of neighborhood environments are linked with a higher risk for several health problems on students, including cognitive deficits (Suglia et al., 2008), which directly affect students' learning performance (Leung et al., 2019).

Among the environmental conditions, green spaces have been suggested as an essential factor. Green spaces play a vital role in people's social, economic, and physical well-being (Bertram and Rehdanz, 2015). These spaces improve physical and mental health by mitigating environmental threats (e.g., reducing air pollution, reducing noise, microclimate regulation, stormwater runoff), providing access to recreational opportunities, and facilitating social cohesion (Carrus et al., 2015; Jennings and Bamkole, 2019). Epidemiological investigations have shown that green spaces are linked with cognitive function. For example, in the US, a cohort study that included 13,594 women found that increasing green space was associated with higher scores of overall cognition and psychomotor speed/attention(Jimenez et al., 2022). In Barcelona, Spain, this benefit from green spaces was related to cognitive development (progress working in memory) in children (Dadvand et al., 2015) . Similar results were found in children participating in a prospective Belgian birth cohort (Dockx et al., 2022). Based on this plausible mechanism related to green space and cognition, studies have reported that schools located in areas with a low density of green spaces are more likely to have students with low learning performance (Browning and Rigolon, 2019; Markevych et al., 2017).

Possible mechanisms for the positive effects of greenness and academic performance may be related to the Attention Restoration Theory – ART and Stress Reduction Theory - SRT (Kaplan, 1995). In short, the ART theory identifies directed attention as the cognitive mechanism that is restored by interactions with nature, while the SRT is related to stress reduction by interactions with nature (Berman et al., 2008). Psychological investigations have associated a vital role for directed attention and stress reduction in school success (Amicone et al., 2018; Diamond et al., 2007; Moreno et al., 2018). Another mechanism is related to the mitigation pathway, which considers the potential capacity of plants in reducing air pollution, noise, and heat (Luque-García et al., 2022). These mediator pathways can influence academic achievements by the health effects that directly impair learning performance. Studies have shown that exposure to air pollution, noise, and heat impacts brain development (Van Den Bosch and Meyer-Lindenberg, 2019), resulting in later neurophysiological effects during infancy and adolescence, such as reductions in brain white matter volume, cognitive impairments, and increases in hyperactivity disorder symptoms (Peterson et al., 2015). This exposure during childhood and teenage years is associated with systemic and central nervous system inflammation, indicating a direct effect on important brain functions (Calderón-Garcidueñas et al., 2012). Finally, the ART and SRT theories suggest the instoration pathway, which considers the benefits of greenness in promoting physical activity and social cohesion (Luque-García et al., 2022).

The existing literature on green space and academic performance still presents mixed results. A review study in 2019 identified 13 peer-reviewed articles that estimated the associations between academic performance and green spaces around schools (Browning and Rigolon, 2019). The investigations assessed in this review study include non-significant/significant associations and positive/negative associations. For example, in Germany (city of Munich and city of Wesel), statistically significant associations were estimated with greenspace exposure (using Normalized Difference Vegetation Index – NDVI, as green space metric) and maths grades in Munich students, but no associations were observed in Wesel children (Markevych et al., 2019). In the District of Columbia (USA), advanced scores in math and reading tests were linked with green spaces (using tree canopy cover and grass/shrub cover, as green space metric) (Kweon et al., 2017). In Chicago (USA), greenspaces (NDVI, as green space metric) were associated with better school performance in math and marginally statistically significant results for standardized tests of reading (Kuo et al., 2018). In New Zealand, week association between greenspace (using land cover database as green space metric) and academic achievement, with some analysis suggesting negative correlations between academic performance and greenspace (Beere and Kingham, 2017).

Besides these mixed results, some studies have suggested that the relationships between urban vegetation and academic achievement is complex and sensitivity to several conditions, including environmental characteristics, socio-economic aspects, and even the type of the study design (e.g., green space metric). For example, (Hodson and Sander, 2021) show that urban vegetation cannot be equally used to support academic achievement. The authors assessed 1,333 public high schools in the USA and found that the relationship between academic achievement and vegetation varied depending on the social, economic, and environmental context surrounding those schools (e.g., vegetation type, built intensity, tree-cover settings, and agricultural settings) (Hodson and Sander, 2021). Another factor influencing the greenspace-academic performance is the type of metric used to measure greenspace, including the type of remote sensing measurement.

To further research on this matter, in this paper, we estimated the association of greenness and academic performance at the school-level in Brazil, where to our knowledge, no study has considered this topic to date. Further studies in low and middle-income countries (e.g., Brazil) are essential to provide better support for policymakers to improve the quality of the environment and education achievements. First, Brazil has a large student population, and environmental conditions may be impacting this population's education success. According to the Brazilian Ministry of Education, Brazil has 47.8 million students (from primary to high school). For comparison purposes, in the United States, according to the Census Bureau in 2017, there are 76.4 million students nationwide enrolled in American schools. Also, Brazil has a considerable difference in the quality of the environment across different populations, influencing health/environment equity negatively. This is an important determinant of the greenness impacts on children’s health, incondign cognitive performance.

2. MATERIALS AND METHODS

2.1. Data

2.1.1. School-level academic performance

School-level academic performance was obtained from the High School National Exam, shortened as ENEM in Brazil (*Exame Nacional do Ensino Medio*). The ENEM is an annual, non-mandatory, and standardized Brazilian national exam managed by the National Institute for

Educational Research in Brazil, known as INEP - *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (a governmental agency under the Brazilian Ministry of Education), with the purpose to evaluate the level of knowledge of the high school students in Brazil. The ENEM is used as an admission exam for enrollment in several universities in Brazil. On average, about 3.5 million students take the ENEM test annually. The ENEM exam includes more than 150 multiple-choice questions.

This school-level academic performance data includes the annual average of ENEM scores by schools for each subject (we assessed sciences and math) between 2009 and 2015. ENEM report scores from other areas (e.g., Human sciences, Portuguese, and foreign languages) were not considered in our analysis because these data presented some inconsistencies, especially temporal discrepancies. We used these averages to represent the school-level academic performance in our analysis. These averages were estimated with the following equation:

$$SAP_{s,z,t} = \frac{\sum_i SC_{i,s,z,t}}{NS_{s,z,t}} \tag{1}$$

where *SAP* is the School-level Academic Performance for the year *t* based on the average ENEM score in the year *t*, from each school *s*, and for each subject *z*. Note that this average was estimated accounting for the sum of ENEM scores from each student *i*, in the subject *z*, at the school *s*, in the year *t;* divided by the number of students at the school *s*, who took the test for the subject *z* in the year *t*. The SAP ranges from 0 to 1,000, of which 0 is the lowest ENEM score, and 1,000 indicates the highest ENEM score.

The INEP calculated these averages only for the high schools with at least 2% of its students who took the ENEM test. After applying this inclusion criterion, the final dataset encompassed a total of 10,549 schools across Brazil, with an average of 140 students per school.

The academic performance data includes categorical variables representing the region where the school is located (urban or rural areas), the type of school (public or private school) and the geographical location (latitude and longitude) of each school. Using the geographical location, we mapped the spatial distribution of the schools, and then estimated the exposure and cofounder variables. These procedures are described in the following sections.

2.1.2. Green areas

We used the Normalized Difference Vegetation Index (NDVI) to estimate greenness around each school. This vegetation index is the normalized ratio of the NIR and red reflectance bands, where NIR and RED are the surface bidirectional reflectance factors from the near-infrared and red (visible) bands, respectively (Huete et al., 2002). The NDVI is considered the most consistent satellite-derived indicator of the greenness level on the ground (Huete et al., 2002; Tian et al., 2015; Zhang et al., 2017) and has been used as a marker for exposure to green spaces in previous epidemiological studies (Browning et al., 2018; Jimenez et al., 2020; Markevych et al., 2017; Wilker et al., 2014; Wu et al., 2014). The NDVI varies between -1 and 1, where negative values correspond to water, dead plants, urban areas (e.g., buildings etc.); values near zero correspond to barren areas of rock or sand, and positive values corresponding to more vegetated or greener regions (1 represents the greenest area). For this study, we use the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data from the Terra satellite (MODIS MOD13Q1 product) and Aqua satellite (MODIS MYD13Q1 product). The data is on a 250 m × 250 m grid worldwide, between 01-Jan-2000 and 31-Dec-2015, with a temporal resolution of 16 calendar days. The dataset includes information on the pixel reliability (8-bit signed integer), with values related to presence of clouds, snow, ice, insignificant data (restriction to be used), and significant data (no restriction).

We calculated the annual average NDVI for the months representing the school year (February–June, August-November) in Brazil between 2009 and 2015. Given that in Brazil there is no well-defined four seasons (winter, spring, summer, and fall), like in the North Hemisphere, the annual variation of NDVI is homogeneous over the year. Then, we estimated the average NDVI of all the pixels around the schools in a buffer of 1 km. Figure 1 illustrates the surfaces of NDVI and the distribution of schools considered in our study.

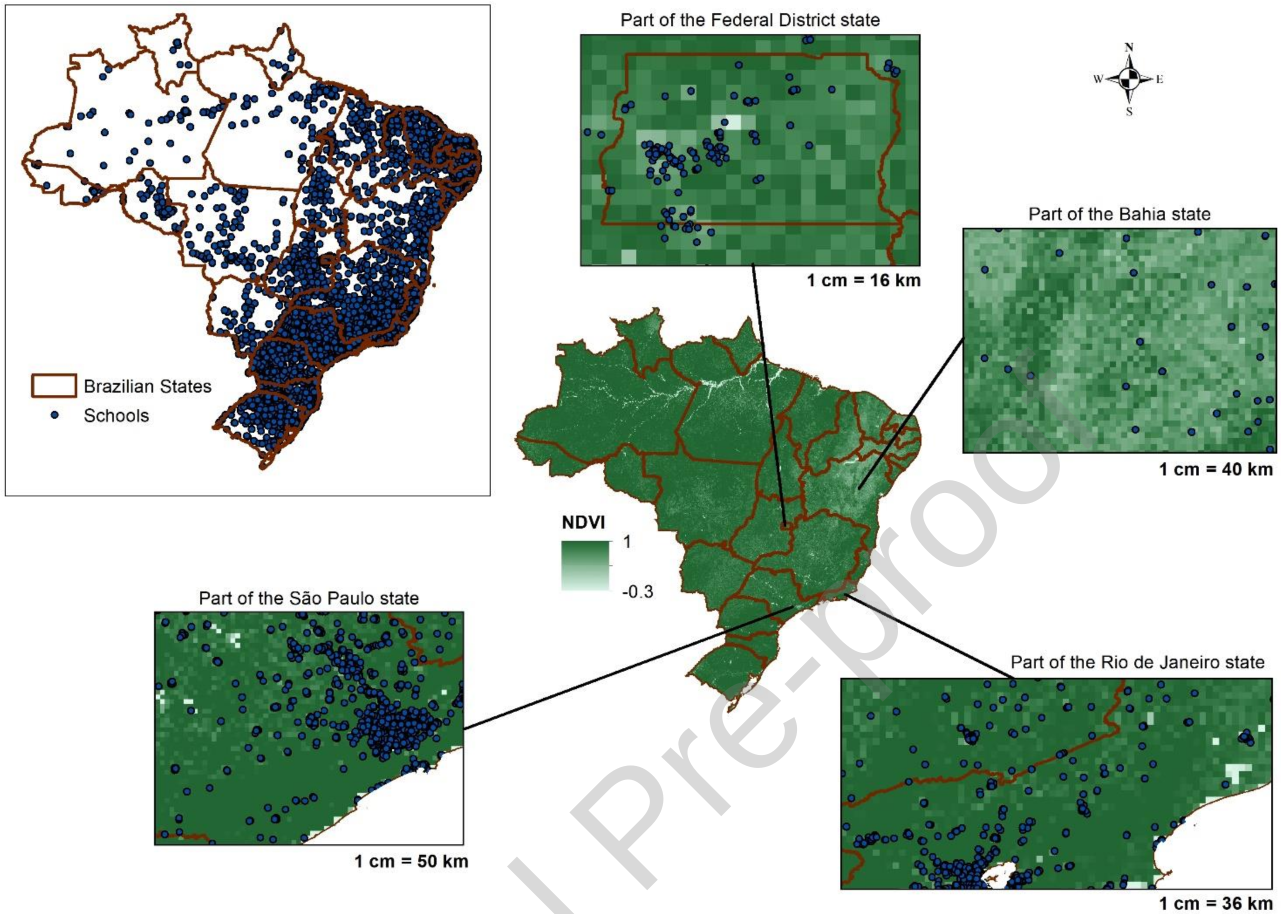

Figure 1 – Spatial distribution of the schools and NDVI level (average 2009-2015) in Brazil.

Note: to provide a better perspective (a fine spatial scale) of the spatial distribution of NDVI values and schools, we highlight four regions in Brazil, including part of the Federal District state, Bahia state, São Paulo state, and Rio de Janeiro state.

2.1.2. Covariates/controlling factors

We accounted for the following variables as potential confounders/controlling factors: region where the school is located (urban or rural areas), type of school (public or private schools), a socioeconomic index, income, education, and Human Development Index (HDI) specifically for HDI-education. As mediator, we accounted for air pollution ($PM_{2.5}$).

The categorical variables representing the region where the school is located and the type of school were provided by the ENEM, in the school-level academic performance data (as we mentioned above). The latitude and longitude information were also included in this dataset. We considered these variables to control for different study conditions in different schools, including the different spatial socio-economic and cultural background.

Air pollution data were assessed from the global model performed by (van Donkelaar et al., 2015). This model was derived from satellite remote sensing observations at 0.01-degree x 0.01-degree spatial resolution. The model estimates the annual mean ambient concentration of $PM_{2.5}$ by combining Aerosol Optical Depth (AOD) retrievals with a chemical transport model, and then calibrated to ground-based observations of $PM_{2.5}$ using Geographically Weighted Regression (GWR). We assigned annual $PM_{2.5}$ concentration to each school included in our analysis by using spatial join. This join was based on the school location and the spatial distribution of the grids with $PM_{2.5}$ information. As result, for each school we included $PM_{2.5}$ information along with NDVI levels. Air pollution exposure was included as a potential mediator in our analysis. Studies have shown that health benefits of green space are mediated by the impact of green spaces on air pollution (Heo and Bell, 2019; Son et al., 2021).

The INEP provided the socioeconomic index. This data indicates the socioeconomic level of each school. This socioeconomic indicator at the school level is known in Brazil as INSE (*Indicador de Nível Socioeconômico*). It comprises four group of schools, of which group 1 represents the schools with the lowest socioeconomic status level and group 4 the schools with the highest socioeconomic level.

Income (average income measured in Brazilian currency, R$, at municipality level), education (percentage of the population in homes where nobody has completed the primary school), and HDI-education were accessed from the Human Development Atlas in Brazil (http://www.atlasbrasil.org.br/2013/en/download/). This dataset is structured by the United Nations Development Program (UNDP) and by the Brazilian Institute for Applied Economic Research (IPEA). The data is at the municipality scale. We intersected this data based on the municipality where the school is located. There are 5,572 municipalities in Brazil, which represent the smallest areas considered by the Brazilian political system. As result, we created the final dataset for the statistical analysis, including NDVI level, $PM_{2.5}$ concentration, and socio-economic variables.

All these variables representing the socioeconomic status (SES) were included as a confounder in our model. A large body of epidemiological literature indicates that population with lower SES are more likely to be exposed to different levels of environmental exposure (Hajat et al., 2021).

2.2. Statistical analysis

We analyzed the association between greenness (represented by NDVI) and school-level academic performance using mixed-effects regression models. The model was adjusted for the variables mentioned in previous section and for other variables contained in the school dataset, including a categorical variable indicating the number of students enrolled in each school (1-30 students, 31-60 students, 61-90 students, and more than 90 students), a categorical variable indicating whether the school is managed by the government (public schools) or by the private sector (private schools). In addition, as a temporal term, we adjusted the model for the year (2009-2015). To represent the spatial terms, we adjusted the model for the Brazilian states where the schools are located and for the type of land use (schools in urban areas and schools in rural areas). We defined a random intercept and slope to vary depending on the municipality in Brazil where the school is located. Equation 2 describes the statistical model.

$$y_{m,z} = \beta_{0[m],z} + \left(\beta_{1[m],z} NDVI\right) + \left(\beta_2 PM25\right) + s_{1,z}(Year) + s_{2,z}(income) + s_{3,z}(education) + s_{4,z}(HDI) + \gamma_z State + \sigma_z Managment + \omega_z Land\ Use + \partial_z NStud + \vartheta_z INSE + \mathrm{e}_{\mathrm{z,m}} \quad (2)$$

where y is the school-level academic performance for the school in the municipality m, for the subject z; β_0 is the intercept coefficient for subject z varying by municipality m; β_1 is the slope coefficient for NDVI, for each subject z, which varies by municipality m; β_2 is the slope coefficient for $PM_{2.5}$; *s()* are the smoothing spline function to characterize nonlinear relationships between academic performance (for each subject z) and year, income, education, and HDI; γ, σ, ω, ∂, and ϑ are the vectors of coefficients that represent the state where the schools are located, the type of management (public or private schools), land use, a categorical variable representing the number of students enrolled in each school, and the socioeconomic indicator INSE, respectively. The statistical analyses were run in R Version 4.0.0.

Specifically for $PM_{2.5}$, we have tested its mediated effects. First, we tested the total effect by looking if any change in green space impacts school-level academic performance at all. Here we did not account for $PM_{2.5}$ in the model. Then, we tested the effect of green spaces on air pollution. Finally, we simultaneously tested the effect of green space and $PM_{2.5}$ on academic performance.

We have checked the assumptions of the mixed-effects model used in this study, including independence of the data points, linearity of the relationship between predictor and response, homogeneity of the residuals, and independence of the random effects versus covariates (exogeneity).

We also applied an autocorrelation test for the residuals from each municipality to evaluate if spatial autocorrelation within municipalities is a problem for our p-values. Finally, we conducted sensitivity analysis by stratifying the analyses by land use and school management type.

3. RESULTS

We accounted for 10,549 schools across Brazil. Among those, 10,136 are urban schools, 413 are in rural areas, 3,579 are private schools, and 6,970 are public schools. NDVI around the schools varies from-0.23 to 0.87, with an average of 0.36 (SD=0.13). School-level academic performance has a significant range, in which for science the variation was from 357 to 723 and for math varied from 257 to 833. Table 1 shows descriptive statistics for the academic performance, NDVI, $PM_{2.5}$, and SES variables.

Table 1 – Descriptive statistics of the school-level academic performance (stratified by subjects), NDVI, $PM_{2.5}$, and SES variables.

Variables		Minimum	Mean	Standard deviation	Maximum
Academic performance	Science	357.00	489.60	50.59	723.70
	Math	357.8	511.10	71.72	833.60
Exposure	NDVI	-0.23	0.36	0.13	0.87
Cofounder	$PM_{2.5}$ (µg/m^3)	2.00	9.47	3.89	30.00
SES variables	Income (R$)	0.00	801.70	391.05	2,043.70
	Education (%)	0.00	27.59	12.05	76.22
	HDI	0.00	0.64	0.09	0.82

After adjustments for the covariates, the primary analysis results indicate that the presence of green areas surrounding schools is positively associated with school-level academic performance in math, with an estimated coefficient of 17.18 (95%CI: 10.46; 23.90). On the other hand, the results were statistically insignificant for science, with a coefficient of -2.39 (95%CI: -7.49; 2.71). The results from the mixed-effects model with random intercept and slope are shown in Table 2, containing the coefficients with the 95% confidence intervals, the p-values, and the random effects. The validity of the mixed-effects model for math grades (the one statistically significant) is shown in Figure 2. The results shown in Table 2 e Figure 2 are from the model with $PM_{2.5}$ as mediator variable. As we mentioned in the methods section, we tested the effect of the green areas on $PM_{2.5}$ and found robust associations. So, we assumed that the mediation by $PM_{2.5}$ occurs when we are looking the association between NDVI and academic performance.

Table 2 – Coefficients of NDVI from the mixed-effects model (primary analysis).

Subject	Estimates	Lower 95%CI	Upper 95%CI	P-value	Random Effects (σ^2)
[1]Science	-51.83	-59.90	-43.71	$p < 0.001$	2,766.34
[1]Math	-39.41	-50.70	-28.20	$p < 0.001$	4,335.94
[2]Science	-2.39	-7.49	2.71	0.36	562.92
[3]Math	17.18	10.46	23.90	$p < 0.001$	560.58

Note: unadjusted model (1), adjusted model with the covariates mentioned in the methods section (2).

The associations between NDVI and school-level academic performance in the primary and sensitivity analyses are shown in Figure 3. As for the primary analysis, we estimated significant positive associations for performance in math in the analyses stratified by private, public, and urban schools. However, for performance in science, the associations persisted with no statistical significance in the coefficients.

Comparing the difference of the NDVI effect between public and private schools specifically for performance in math, our results suggest that private schools have the highest effects from NDVI. We could not perform this comparison based on the land use because the model stratified by schools in rural areas did not converge due to the number of observations (Figure 3).

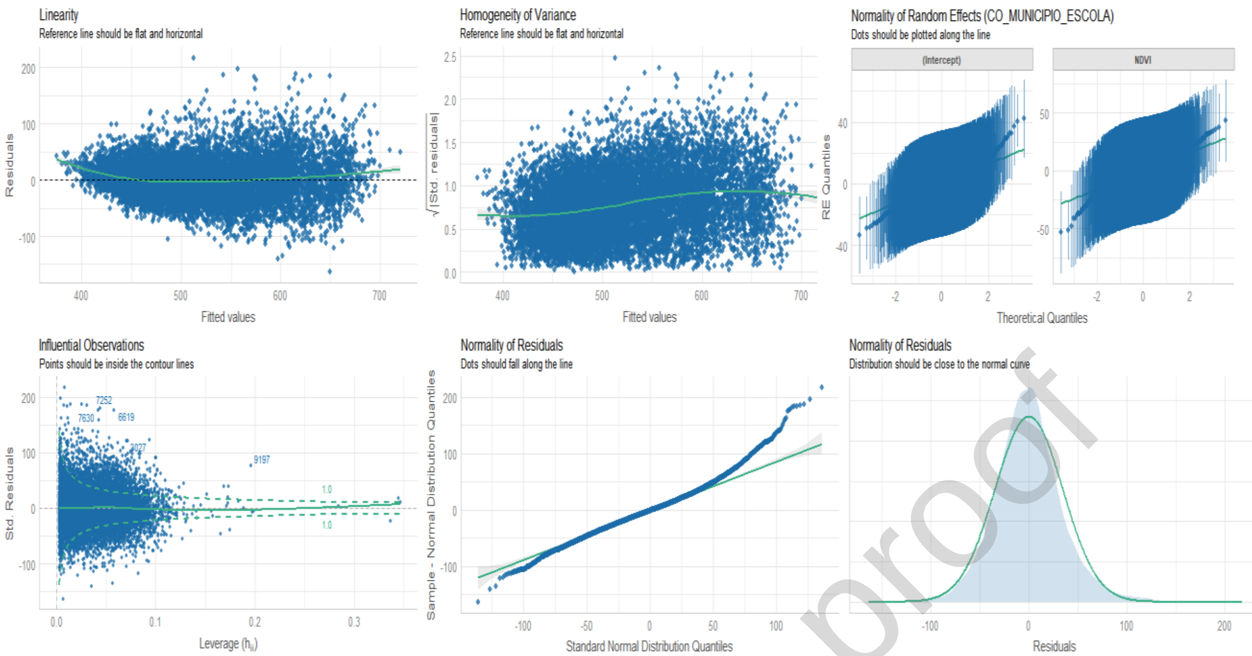

Figure 2 – Validity of the mixed-effects model for math grades, including the test of linearity, homogeneity of variance, normality of random effects, influential observations, and normality of residuals.

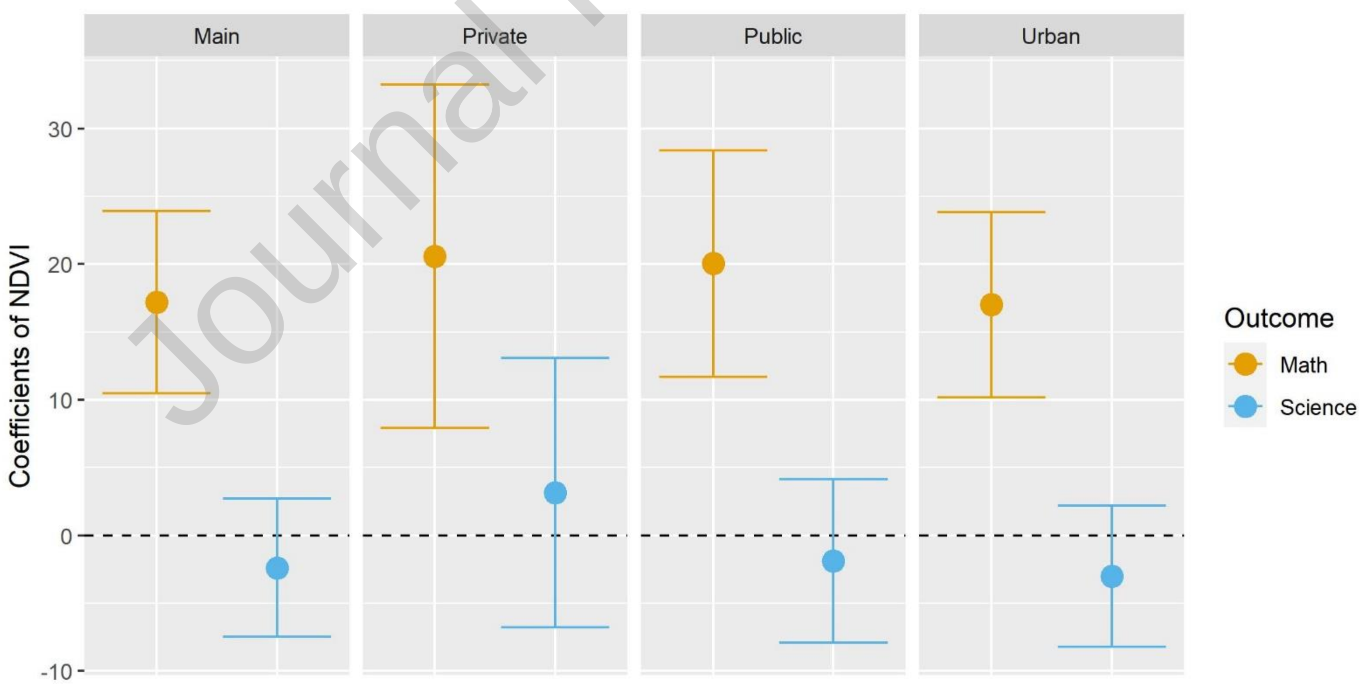

Figure 3 – Effects of NDVI on school-level academic performance in Brazil (primary and sensitivity analysis stratified by subjects).

Notes: primary analysis (Main), sensitivity analysis stratified by private schools (Private), sensitivity analysis stratified by public schools (Public), sensitivity analysis stratified by rural schools (Rural), sensitivity analysis stratified by urban schools (Urban).

4. DISCUSSION

Our findings suggest relationship between green areas surrounding schools in Brazil and student academic performance in Math. This result varies depending on the type of school (e.g., private and public schools) and type of land use where the school is located (e.g., urban areas). We suggest that population density, connectivity among urban structures, etc. around schools may explain part of this variation. The assumption is that these urbanicity characteristics are proxy indicator of quality of green areas, which describe the land use through the physical (e.g., size) and functional properties (Réquia et al., 2015). A recent study in Maryland, USA, has suggested that the association between green areas and academic performance varies by some factors, including remote sensing measures and urbanicity (Browning and Locke, 2020). All these factors are related to the insufficient statistical controls for the moderating effect of some schools (e.g., disadvantaged schools), including the effects of poverty and race on the academic performance relationship ((Browning et al., 2018). This is because socioeconomic status is strongly correlated with green areas (Hodson and Sander, 2017; Powell et al., 2004). This has been reinforced by a recent review study (Jimenez et al., 2021).

Our results are consistent with the limited number of previous investigations on this topic. In Massachusetts, green areas were positively associated with student's academic performance in English and Mathematics (Leung et al., 2019; Wu et al., 2014). Overall, the coefficients for Mathematics were higher than English (Leung et al., 2019; Wu et al., 2014). Instead of English, in our study, we accounted for academic achievement in science. Here the results were the opposite, which the relationship was null, with negative coefficients for science in the main analysis and in the subgroup analysis for public and urban schools. These mixed results were also found in the investigation performed by (Browning et al., 2018). These discordant associations compared to the analysis focused on math (which the coefficients were positive) may be related to the insufficient statistical controls for the moderating effect of disadvantaged schools, as we mentioned before. The lack of sample size calculation and randomness may be other issues. Finally, there is the possibility that math may be measuring different cognitive processes (e.g., memory and logic are affected differently) which is affected differently by green areas.

Our study has some strengths. First, this is the first study in Brazil linking green areas and school-level academic performance. As we mentioned in the introduction section, a study in Brazil is important given the large student population in the country (47.8 million) and the spatial distribution of the environmental issues that influences health/environment equity negatively. Second, our sample size includes 10,549 schools across Brazil, representing approximately 7% of the Brazilian schools. Third, we accounted for a spatio-temporal analysis with a study period of 7 years (NDVI and school-level academic performance data). Some of the previous investigations have not considered a temporal component. Finally, our framework accounts for a solid quantitative component by estimating how the variance in residuals differs by the municipality, which considers the different types of public educational policies among the schools.

Our results, however, should be interpreted considering some limitations. First, there is a possibility of some residual confounding (even after adjusting for potential confounders, including air pollution, temporal factors, and SES) and selection bias. Here, we point out the possibility that i) the confounding variables are not precise enough (e.g., we accounted for categorical variables to represent the number of students in each school and the socioeconomic indicator INSE) and ii) we may have assumed incorrectly a linear relation between the confounder and academic performance (this was the case for the variable representing the number of students enrolled in each school). Regarding the selection bias, it is because the ENEM is a non-mandatory exam. However, we believe that this bias is not significant. Although the ENEM is a non-mandatory exam, according to the Ministry of Education in Brazil, more than 85% of the high-school students in Brazil take the ENEM test annually. In 2020, Brazil had 7.2 million high-school students. Among those, 6.2 million took the ENEM test. This high number of students taking the exam is because several universities in Brazil use the ENEM test as an admission exam for enrollment. Second, we highlighted that our study has a cross-sectional nature in an ecological setting that does not enable statements about causality. We are just able to suggest associations between greenness and student's performance. Third, we accounted only for one measure of green areas (NDVI), which does not capture the quality of the green area. For example, the NDVI measurement may consider as the same value (e.g., NDVI =0.9, indicating high greenness) some grass in an urban landscape and the Amazon Forest. The influence on the health of grass in an urban landscape and an urban park may be different. We assume that an urban park provides more health benefits than a grass in an urban landscape. This suggests that different green spaces may be more susceptible to the confounding influences of socioeconomic gradients and self-selection bias (Mockrin et al., 2019). Fourth, we accounted for a mix of vegetation within and around schools, given that we used a buffer of 1 km surrounding the centroids of each school and not a buffer surrounding schools. This influences the process to identify if our results are related to school vegetation or surrounding vegetation. However, based on our local knowledge, we assume that overall, the area of the schools in Brazil is much lower than the buffer size of 1 km, which let us indicate that our findings are more related to surrounding vegetation than the school vegetation. Fifth, given the different spatial scales of the variables (student's performance, $PM_{2.5}$, NDVI, SES) in our analyses, there may be a problem of spatial pseudo-replication due to the spatial autocorrelation, which may artificially inflate the p-values. However, we have ran an autocorrelation test for the residuals from each municipality and the results did not indicate the presence of spatial autocorrelation. There is also the limitation related to the buffer size. The effect sizes and statistical significance of our results may vary by different buffer sizes. Also, the INEP calculates averages for schools where at least 2% of the population took the ENEM. This may impact the representativity of our results. However, the INEP reports that, on average, 140 students per school took the test, indicating that most of the schools included in the sample have more than 50% of their students who took the test. Also, we used NDVI provided by MODIS. Compared to other sources, this data has a coarse resolution, with 250 m × 250 m grid. Other remote sensing measure has a higher spatial resolution, including the data from Landsat, with 30 m x 30 m. The remote sensing data that we selected may influence our results, given that surrounding some schools the vegetation may be concentrated in a few pixels, which may result in skewed coefficients (Browning and Locke, 2020). Finally, our findings might not be generalized considering different socio-economical and cultural background or the study conditions in different schools. Therefore, the policy making should account for those variations and recommend targetable guidelines to improve the environment surrounding schools.

5. CONCLUSIONS

Results from our investigation provide epidemiological evidence that high green spaces surrounding schools in Brazil are associated with high school-level academic performance in math. Our findings are relevant for policymakers and urban planners to improve the environment surrounding schools to promote public health by making schools healthier. Furthermore, results from our study can be incorporated into public policies for feasible targeted interventions to those Brazilian students from exposure to environmental hazards and improve their safety, health, and learning performance. Finally, we specify the following guidelines to how our study can benefit policy making i) developtment of green awareness, ii) creation of green infrastructure around schools (e.g., parks and inner-city vegetation), iii) development of multi-criteria models accounting for greenness as a criterion to select better areas to build new schools, and, iv) focus on schools located in areas with inequalities in green space quality.

REFERENCES

Amicone, G., Petruccelli, I., De Dominicis, S., Gherardini, A., Costantino, V., Perucchini, P., Bonaiuto, M., 2018. Green Breaks: The restorative effect of the school environment's green areas on children's cognitive performance. Front Psychol 9, 1–15. https://doi.org/10.3389/fpsyg.2018.01579

Baldauf, R.W., Heist, D., Isakov, V., Perry, S., Hagler, G.S.W., Kimbrough, S., Shores, R., Black, K., Brixey, L., 2013. Air quality variability near a highway in a complex urban environment. Atmos Environ 64, 169–178.

Beere, P., Kingham, S., 2017. Assessing the relationship between greenspace and academic achievement in urban New Zealand primary schools. N Z Geog 73, 155–165. https://doi.org/https://doi.org/10.1111/nzg.12155

Berman, M.G., Jonides, J., Kaplan, S., 2008. The cognitive benefits of interacting with nature. Psychol Sci 19, 1207–1212. https://doi.org/10.1111/j.1467-9280.2008.02225.x

Bertram, C., Rehdanz, K., 2015. The role of urban green space for human well-being. Ecological Economics 120, 139–152. https://doi.org/10.1016/j.ecolecon.2015.10.013

Browning, M.H.E.M., Kuo, M., Sachdeva, S., Lee, K., Westphal, L., 2018. Greenness and school-wide test scores are not always positively associated – A replication of "linking student performance in Massachusetts elementary schools with the 'greenness' of school surroundings using remote sensing." Landsc Urban Plan 178, 69–72. https://doi.org/10.1016/j.landurbplan.2018.05.007

Browning, M.H.E.M., Locke, D.H., 2020. The greenspace-academic performance link varies by remote sensing measure and urbanicity around Maryland public schools. Landsc Urban Plan 195, 103706. https://doi.org/10.1016/j.landurbplan.2019.103706

Browning, M.H.E.M., Rigolon, A., 2019. School green space and its impact on academic performance: A systematic literature review. Int J Environ Res Public Health 16. https://doi.org/10.3390/ijerph16030429

Carrus, G., Scopelliti, M., Lafortezza, R., Colangelo, G., Ferrini, F., Salbitano, F., Agrimi, M., Portoghesi, L., Semenzato, P., Sanesi, G., 2015. Go greener, feel better? The positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. Landsc Urban Plan 134, 221–228. https://doi.org/10.1016/j.landurbplan.2014.10.022

Dadvand, P., Nieuwenhuijsen, M.J., Esnaola, M., Forns, J., Basagaña, X., Alvarez-Pedrerol, M., Rivas, I., López-Vicente, M., de Pascual, M.C., Su, J., Jerrett, M., Querol, X., Sunyer, J., 2015. Green spaces and cognitive development in primary schoolchildren. Proc Natl Acad Sci U S A 112, 7937–7942. https://doi.org/10.1073/pnas.1503402112

Diamond, A., Barnett, W.S., Thomas, J., Munro, S., 2007. The early years: Preschool program improves cognitive control. Science (1979) 318, 1387–1388. https://doi.org/10.1126/science.1151148

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

Hajat, A., Maclehose, R.F., Rosofsky, A., Walker, K.D., Clougherty, J.E., 2021. Confounding by socioeconomic status in epidemiological studies of air pollution and health: Challenges and opportunities. Environ Health Perspect 129, 1–10. https://doi.org/10.1289/EHP7980

Heo, S., Bell, M.L., 2019. The influence of green space on the short-term effects of particulate matter on hospitalization in the U.S. for 2000–2013. Environ Res 174, 61–68. https://doi.org/10.1016/J.ENVRES.2019.04.019

Hodson, C.B., Sander, H.A., 2021. Relationships between urban vegetation and academic achievement vary with social and environmental context. Landsc Urban Plan 214, 104161. https://doi.org/10.1016/j.landurbplan.2021.104161

Hodson, C.B., Sander, H.A., 2017. Green urban landscapes and school-level academic performance. Landsc Urban Plan 160, 16–27. https://doi.org/10.1016/j.landurbplan.2016.11.011

Huete, A., Didan, K., Miura, T., Rodrigues, E., Gao, S., Ferreira, L., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83, 195–213. https://doi.org/10.1080/0965156x.2013.836857

Jennings, V., Bamkole, O., 2019. The relationship between social cohesion and urban green space: An avenue for health promotion. Int J Environ Res Public Health 16. https://doi.org/10.3390/ijerph16030452

Jimenez, M.P., Deville, N. V., Elliott, E.G., Schiff, J.E., Wilt, G.E., Hart, J.E., James, P., 2021. Associations between nature exposure and health: A review of the evidence. Int J Environ Res Public Health 18. https://doi.org/10.3390/ijerph18094790

Jimenez, M.P., Elliott, E.G., Deville, N. v., Laden, F., Hart, J.E., Weuve, J., Grodstein, F., James, P., 2022. Residential Green Space and Cognitive Function in a Large Cohort of Middle-Aged Women. JAMA Netw Open 5, E229306. https://doi.org/10.1001/jamanetworkopen.2022.9306

Jimenez, M.P., Oken, E., Gold, D.R., Luttmann-Gibson, H., Requia, W.J., Rifas-Shiman, S.L., Gingras, V., Hivert, M.-F., Rimm, E.B., James, P., 2020. Early life exposure to green space and insulin resistance: An assessment from infancy to early adolescence. Environ Int 142, 105849. https://doi.org/10.1016/j.envint.2020.105849

Kaplan, S., 1995. The restorative benefits of nature: Toward an integrative framework. J Environ Psychol 15, 169–182. https://doi.org/10.1016/0272-4944(95)90001-2

Kuo, M., Browning, M.H.E.M., Sachdeva, S., Lee, K., Westphal, L., 2018. Might school performance grow on trees? Examining the link between "Greenness" and academic achievement in Urban, high-poverty schools. Front Psychol 9. https://doi.org/10.3389/fpsyg.2018.01669

Kweon, B.S., Ellis, C.D., Lee, J., Jacobs, K., 2017. The link between school environments and student academic performance. Urban For Urban Green 23, 35–43. https://doi.org/10.1016/j.ufug.2017.02.002

Leung, W., Yee Tiffany Tam, T., Pan, W.C., Wu, C. Da, Candice Lung, S.C., Spengler, J.D., 2019. How is environmental greenness related to students' academic performance in English and Mathematics? Landsc Urban Plan 181, 118–124. https://doi.org/10.1016/j.landurbplan.2018.09.021

Luque-García, L., Corrales, A., Lertxundi, A., Díaz, S., Ibarluzea, J., 2022. Does exposure to greenness improve children's neuropsychological development and mental health? A Navigation Guide systematic review of observational evidence for associations. Environ Res 206, 112599. https://doi.org/10.1016/j.envres.2021.112599

Markevych, I., Feng, X., Astell-Burt, T., Standl, M., Sugiri, D., Schikowski, T., Koletzko, S., Herberth, G., Bauer, C.P., von Berg, A., Berdel, D., Heinrich, J., 2019. Residential and school greenspace and academic performance: Evidence from the GINIplus and LISA longitudinal studies of German adolescents. Environmental Pollution 245, 71–76. https://doi.org/10.1016/J.ENVPOL.2018.10.053

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

Mockrin, M.H., Locke, D.H., Stewart, S.I., Hammer, R.B., Radeloff, V.C., 2019. Forests, houses, or both? Relationships between land cover, housing characteristics, and resident socioeconomic status across ecoregions. J Environ Manage 234, 464–475. https://doi.org/10.1016/j.jenvman.2018.12.001

Moreno, A., Baker, S., Varey, K., Hinze-Pifer, R., 2018. Bringing attention restoration theory to the classroom: A tablet app using nature videos to replenish effortful cognition. Trends Neurosci Educ 12, 7–21. https://doi.org/https://doi.org/10.1016/j.tine.2018.07.002

Powell, L.M., Slater, S., Chaloupka, F.J., 2004. The relationship between community physical activity settings and race , ethnicity and socioeconomic status. Evidence-Based Preventive Medicine 1, 135–144.

Requia, W.J., Roig, H.L., Adams, M.D., Zanobetti, A., Koutrakis, P., 2016. Mapping distance-decay of cardiorespiratory disease risk related to neighborhood environments. EnvironmentalResearch 151, 203–215. https://doi.org/10.1016/j.envres.2016.07.038

Réquia, W.J., Roig, H.L., Koutrakis, P., 2015. A novel land use approach for assessment of human health: The relationship between urban structure types and cardiorespiratory disease risk. Environ Int 85, 334–342. https://doi.org/10.1016/j.envint.2015.09.026

Son, J.Y., Choi, H.M., Fong, K.C., Heo, S., Lim, C.C., Bell, M.L., 2021. The roles of residential greenness in the association between air pollution and health: a systematic review. Environmental Research Letters 16. https://doi.org/10.1088/1748-9326/ac0e61

Suglia, S.F., Gryparis, A., Wright, R.O., Schwartz, J., Wright, R.J., 2008. Association of black carbon with cognition among children in a prospective birth cohort study. Am J Epidemiol 167, 280–286. https://doi.org/10.1093/aje/kwm308

Tian, F., Fensholt, R., Verbesselt, J., Grogan, K., Horion, S., Wang, Y., 2015. Evaluating temporal consistency of long-term global NDVI datasets for trend analysis. Remote Sens Environ 163, 326–340. https://doi.org/10.1016/j.rse.2015.03.031

van Donkelaar, A., Martin, R. V, Spurr, R.J.D., Burnett, R.T., 2015. High-Resolution Satellite-Derived PM2.5 from Optimal Estimation and Geographically Weighted Regression over North America. Environ Sci Technol 49, 10482–91. https://doi.org/10.1021/acs.est.5b02076

Wilker, E.H., Mostofsky, E., Lue, S.H., Gold, D., Schwartz, J., Wellenius, G.A., Mittleman, M.A., 2013. Residential proximity to high-traffic roadways and poststroke mortality. Journal of Stroke and Cerebrovascular Diseases 22, e366–e372. https://doi.org/10.1016/j.jstrokecerebrovasdis.2013.03.034

Wilker, E.H., Wu, C. Da, McNeely, E., Mostofsky, E., Spengler, J., Wellenius, G.A., Mittleman, M.A., 2014. Green space and mortality following ischemic stroke. Environ Res 133, 42–48. https://doi.org/10.1016/j.envres.2014.05.005

Wu, C. Da, McNeely, E., Cedeño-Laurent, J.G., Pan, W.C., Adamkiewicz, G., Dominici, F., Lung, S.C.C., Su, H.J., Spengler, J.D., 2014. Linking student performance in Massachusetts elementary schools with the “greenness” of school surroundings using remote sensing. PLoS One 9, 1–9. https://doi.org/10.1371/journal.pone.0108548

Zhang, Y., Song, C., Band, L.E., Sun, G., Li, J., 2017. Reanalysis of global terrestrial vegetation trends from MODIS products: Browning or greening? Remote Sens Environ 191, 145–155. https://doi.org/10.1016/j.rse.2016.12.018

Author Statement

WJR contributed to the conceptualization, methodology, data curation, reviewing and editing of the manuscript. Prepared the original draft. CCS contributed to the data wrangling and model development.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Highlights

- This is the first study in Brazil linking green areas and school-level academic performance
- We accounted for a spatio-temporal analysis with a study period of 7 years
- Green areas are positively associated with school-level academic performance in math.
- The results were statistically insignificant for science.
- Our findings are relevant for policymakers and urban planners to improve the environment surrounding schools.