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Schools exposure to air pollution sources in Brazil: A nationwide assessment of more than 180 thousand schools

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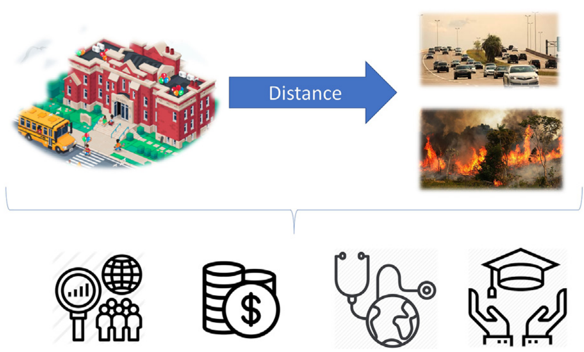
HIGHLIGHTS

- We estimate the exposure to air pollution sources at 186,080 schools in Brazil.
- 25% of the Brazilian schools evaluated in our study are located within a distance ≤250 m of a major roadway.
- 25% of the Brazilian schools evaluated in our study have ≥7 wildfires records within a buffer of 10 km.
- We evaluated the exposure for more than 40 million students who attended Brazilian schools in 2015.
- Approximately 10 million students were likely to be exposed to high levels of air pollution from traffic and wildfire.

GRAPHICAL ABSTRACT



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ABSTRACT

A growing body of evidence demonstrates that children at schools who are exposed to increased concentrations of air pollutants may have a higher risk for several health problems, including cognitive deficits. In this paper we estimate the exposure to air pollution sources at 186,080 schools in Brazil. Specifically, we accounted for the exposure to three proxies of air pollution source emissions, including distance to roadways, the extent of roadways within a buffer around each school, and the number of wildfire occurrences within a buffer around each school. About 25% of the Brazilian schools evaluated in our study are located within a distance ≤250 m of a major roadway, have ≥2 km of roadway within a buffer of 1 km, and have ≥7 wildfires records within a buffer of 10 km. Our results indicate significant prevalence ratio of these schools exposed to air pollution sources when we stratified the analyses by socioeconomic factors, including geographic (public schools had an increased likelihood of being exposed), economic (low-income areas had an increased likelihood of being exposed), health (overall, areas with low public health status had an increased likelihood of being exposed), and educational conditions (overall, areas with low educational indicator had an increased likelihood of being exposed). For example, we estimated that private schools were 15% (95% CI: 13–17%) less likely to be located within 250 m of a major roadway compared with public schools; schools in areas with low child mortality were 35% (95% CI: 34–37%) less likely to be within 250 m of a major roadway; and schools in regions with low expected years of schooling were 25% (95% CI: 22–28%) more likely to be located within 250 m of a major roadway. The analysis of the spatial patterns shows that a substantial number of schools (36–54%, depending on the air pollution source) has a positive autocorrelation, suggesting that exposure level at these schools are similar to their neighbors. Estimating children's exposure to air pollutants at school is crucial for future public policies to develop effective environmental, transportation,

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educational, and urban planning interventions that may protect students from exposure to environmental hazards and improve their safety, health, and learning performance.

1. Introduction

Human exposure to air pollution source emissions has been associated with numerous chronic (Laumbach and Kipen, 2012; Xu et al., 2016) and acute (Lee et al., 2015; Weichenthal et al., 2014) health effects. People with pre-existing health conditions (Pope et al., 2015), older adults (Bell et al., 2014), and children (Du et al., 2012; Svendsen et al., 2012) are considered the most vulnerable population groups who experience a greater risk of morbidity and mortality compared with the general population.

Population exposure to sources of air pollution has significant variation over space and population groups (Burnett et al., 2018; Marshall et al., 2014). Studies have shown that its disparity can be determined by geographical factors, including people's location (Soares et al., 2014; Zou et al., 2014). For example, while adults spend a large portion of the day at workplaces and homes, and these locations can be considered areas where they receive most of their exposure (Requia et al., 2017b), for children and adolescents, the greatest exposure occurs in another indoor environment - at schools (Adams and Requia, n.d.; Requia et al., 2017a).

Air pollution around schools is a crucial concern worldwide. Studies have shown that numerous schools are located in areas with a high level of air pollutants (Guo et al., 2010; Richmond-Bryant et al., 2009; Rivas et al., 2014). Most of these studies have used distance to road as a proxy variable to represent a source of air pollution. For example, in the United States, a nationwide survey of nine large metropolitan areas found that 30% of the schools are within 400 m of a major roadway (important indicator of air pollution), and over 10% are within 100 m (Appatova et al., 2008). In Canada, Amram et al. (2011) assessed 1556 public elementary schools and reported that 16.3% of schools are located within 75 m of a major road. Other investigations have accounted for direct air pollution metrics (e.g., mass or concentration of air pollutants) to assess the exposure to air pollution at schools. For example, Requia et al. (2017a) evaluated $PM_{2.5}$ intake fractions (iF) for vehicular emissions in 32,298 students from 86 elementary schools in Hamilton, Canada. The authors showed that, on average, each student inhales 13.06 ppm (this is the unit when studies account for iF approach) daily during class hours (indoor exposure at schools presented the highest iF). Raysoni et al. (2016) show that while indoor $PM_{2.5}$ concentrations at schools in Quito, Ecuador, ranged from 0.4 μg/m^3 to 72.1 μg/m^3, the outdoor $PM_{2.5}$ concentrations varied from 4.0 μg/m^3 to 34.6 μg/m^3.

Wildfire is another source of air pollution that is potentially hazardous for children. Emissions from forest fires can travel over large distances, affecting air quality and human health far from the originating fires (Youssouf et al., 2014). Fine particulate matter ($PM_{2.5}$) is the major pollutant emitted by wildfires. In the United States, according to the National Emissions Inventory (NEI), in 2014 wildfires represented more than 20% of total $PM_{2.5}$ emissions annually (EPA, 2014). While quantification about schools' exposure to wildfire emissions is very limited, some studies have focused on the health impacts of wildfire emissions on the general population. For example, Liu et al. (2017) estimated a 7.2% increase in risk for respiratory admissions during smoke wave days with high wildfire-specific $PM_{2.5}$ (>37 μg/m^3) compared to matched non-smoke wave days during 2004 and 2009 in the Western U.S. In Southern California, children's exposure to the wildfire smoke in 2003 was associated with increased eye and respiratory symptoms, medication use, and physician visits (Künzli et al., 2006).

A growing body of evidence demonstrates that children at schools who are exposed to increased concentrations of air pollutants may have a higher risk for several health problems, including cardiorespiratory diseases (Andersen et al., 2007; Fan et al., 2016), dysfunction (Lin et al., 2013), acute neuropsychological effects (Sunyer et al., 2017), and cognitive deficits (Calderón-Garcidueñas et al., 2008; Suglia et al., 2008). For example, Mohai et al. (2011) found that schools located in areas with the highest air pollution levels in Michigan, United States, presented the lowest academic performance. In California, children who live within 500 m of a freeway have substantially reduced lung development (Gauderman et al., 2007). Wang et al. (2009) showed a significant relationship between chronic low-level traffic-related air pollution exposure and neurobehavioral function in children at schools in Quanzhou, China. In Porto, Portugal, exposure to $PM_{2.5}$ and PM_{10} at schools (indoor air pollution) were associated with higher odds of respiratory symptoms in children (Madureira et al., 2015).

Estimating children's exposure to air pollutants at school is crucial to advance environmental health effects research and by providing evidence to develop school and environmental policies that will protect children from exposure to environmental hazards. Although some environmental studies have estimated the level of air pollution exposure at schools, others have used distance to road as a proxy variable for air pollution exposure, and others have examined its health effects on students, we are unaware of studies that have looked at the Brazilian population. As we described above, most of the studies were performed in the USA. Also, to our knowledge, there are no investigations (even in the U.S.) that have assessed the spatial patterns of the school's exposure to different air pollution sources (most of the studies have considered only distance to road) by stratifying the exposure level by different socio-economic factors. To address this research gap, in this paper we estimate the exposure to air pollution sources at more than 180 thousand schools in Brazil. Specifically, we accounted for the exposure to three proxies of air pollution source emissions, including distance to roadways, the extent of roadways within a buffer around each school, and the number of wildfire occurrences within a buffer around each school. We assessed the social variation of school exposure to distance to roadways and wildfire by stratifying the results by 12 socio-economic factors, including geographic, demographic, health, and educational conditions. Then, we evaluated the spatial patterns of the exposure at the Brazilian schools.

2. Materials and methods

2.1. School data

School data were obtained from the National Institute for Educational Research in Brazil (http://portal.inep.gov.br/web/guest/inicio), known as INEP - *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira*. This institute is a governmental agency under the Brazilian Ministry of Education.

The school dataset included a list of addresses (including street number, city, state, and postal code) for 186,080 schools grouped by schools in urban areas and schools in rural areas in Brazil. This list includes public and private schools for the following educational stages: early childhood education - preschool, elementary school, middle school, and high school. Using the addresses from each school, we geocoded the data by spatially creating the latitude and longitude for each school and displaying the schools over Brazil.

The school dataset also includes a categorical variable representing the number of students. This variable has four categories – 0-100 students, 101–300 students, 301–800 students, and more than 800 students. We converted these categories into the following numbers, 50, 150, 550, and 1000 students, respectively.

Table 1
Summary statistics for the air pollution source emissions data.

	Distance to road (m)	Extent of road (km)	Wildfire occurrences within 10 km
Minimum	0	0	0
First quartile	260.20	0	1.00
Mean	4166.70	1.43	6.25
Standard deviation	21,522.76	1.41	10.29
Third quartile	1386.00	2.07	7.00
Maximum	380,230.70	10.81	132.00

2.2. Socio-economic data

Socio-economic data 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 Programme (UNDP) and by the Institute for Applied Economic Research (IPEA). These data include numerous indicators about demographic, education, income, employment, housing, and vulnerability in the Brazilian municipalities extracted from the demographic censuses of 1991, 2000, and 2010. We accounted for the data from the last census (2010) and the following socio-economic indicators: Gross Domestic Product (GDP) per capita, income (in Brazilian currency, Real, R$), population, child mortality (mortality rate of children under the age of five), probability of survival up to 40 years old, expected years of schooling (number of years of schooling that a child of school entrance age can expect to receive if prevailing patterns of age-specific enrolment rates persist throughout the child's life), percentage of the population in the elementary school and middle school (6–14 years old) that is not over-age, percentage of children (4–5 years old) that is not going to school, percentage of children (6–14 years old) that is not going to school, and Human Development Index (HDI). Using spatial join techniques, we aggregated these data by school, based on the municipal district where each school is located.

2.3. Air pollution source data

As described above, we accounted for three variables to represent air pollution exposure at Brazilian schools. We describe each air pollution exposure data in the following sections.

2.3.1. Distance to major roadway

Using Geographic Information System (GIS) techniques we estimated the straight-line distance between each school and the nearest major roadway. The road spatial data was provided by the Brazilian Ministry of Infrastructure (http://transportes.gov.br/bit/63-bit/5124-bittemas.html).

2.3.2. Extent of major roadway

We used the same road network data provided by the Brazilian Ministry of Infrastructure (described above) to estimate the extent of major roadway around each school. This estimation was performed by GIS techniques. First, we generated buffers of 1 km around each school and then we calculated the extent (km) of all major roadway inside the buffers.

2.3.3. Wildfire

Wildfire data were provided by the National Institute of Spatial Research (INPE) of Brazil (http://queimadas.dgi.inpe.br/queimadas/portal). The data obtained contain wildfire records, including the date of wildfire occurrence (we used the data from 2015) and the geographical location. These data are derived from seven satellite remote sensing observations, including NOAA-18, NOAA-19, METOP-B, MODIS (NASA TERRA and AQUA), VIIRS (NPP-Suomi and NOAA-20), GOES-16, and MSG-3. We use GIS techniques to summarize the number of wildfire occurrences inside buffers with 10 km (buffers around each school).

2.4. Statistical analysis

2.4.1. Prevalence ratio of a school being exposed to air pollution sources

We calculated the prevalence ratio and 95% confidence intervals (CI) to estimate the association between school-level indicators of socioeconomic status and the probability of a school being near a major roadway,

Table 2
Number of schools and students by air pollution sources and stratification parameters.

Stratification parameter		Distance to roadway (≤250 m)				≥2 km of roadway within 1 km				≥7 wildfires within 10 km			
		Schools		Students		Schools		Students		Schools		Students	
		N	%	N	%	N	%	N	%	N	%	N	%
Land use	Urban	27,996	15.05	9,130,450	19.10	29,584	15.90	9,673,400	20.23	23,753	12.76	8,467,100	17.71
	Rural	16,822	9.04	1,676,700	3.51	16,944	9.11	1,736,600	3.63	22,394	12.03	2,199,900	4.60
School type	Private	8493	4.56	1,848,150	3.87	9274	4.98	1,996,900	4.18	6814	3.66	1,506,100	3.15
	Public	36,325	19.52	8,959,000	18.74	37,254	20.02	9,413,100	19.69	39,333	21.14	9,160,900	19.16
GDP per capita	<Q1	13,040	7.01	2,242,150	4.69	12,579	6.76	2,187,450	4.57	19,938	10.71	3,253,100	6.80
	>Q3	8428	4.53	2,663,850	5.57	8586	4.61	2,682,750	5.61	5903	3.17	2,062,100	4.31
Income	<Q1	11,163	6.00	2,198,000	4.60	10,282	5.53	2,095,850	4.38	15,746	8.46	2,672,950	5.59
	>Q3	7937	4.27	2,556,600	5.35	8247	4.43	2,652,800	5.55	6169	3.32	2,265,050	4.74
Population	<Q1	13,189	7.09	2,450,300	5.12	11,106	5.97	2,095,550	4.38	12,687	6.82	2,145,250	4.49
	>Q3	6756	3.63	2,353,850	4.92	7103	3.82	2,470,550	5.17	8273	4.45	3,040,400	6.36
Child mortality	<Q1	9123	4.90	2,666,300	5.58	9514	5.11	2,809,200	5.88	4359	2.34	1,325,100	2.77
	>Q3	13,618	7.32	2,446,050	5.12	13,237	7.11	2,415,550	5.05	19,164	10.30	3,169,400	6.63
Probability of survival up to at 40 years old	<Q1	12,896	6.93	2,886,200	6.04	12,142	6.53	2,846,150	5.95	12,157	6.53	2,291,750	4.79
	>Q3	9533	5.12	2,677,100	5.60	10,262	5.51	2,997,050	6.27	12,586	6.76	3,815,800	7.98
Expected years of schooling	<Q1	12,658	6.80	2,266,300	4.74	12,183	6.55	2,310,150	4.83	16,443	8.84	2,790,350	5.84
	>Q3	10,115	5.44	2,734,150	5.72	10,045	5.40	2,784,450	5.82	6254	3.36	1,693,350	3.54
% of the population (6–14 years old) that is not over-age	<Q1	12,711	6.83	2,282,250	4.77	11,988	6.44	2,213,850	4.63	17,554	9.43	2,932,450	6.13
	>Q3	9716	5.22	2,691,550	5.63	9433	5.07	2,651,300	5.55	5299	2.85	1,554,550	3.25
% of children (4–5 years old) that is not going to school	<Q1	12,627	6.79	3,003,650	6.28	13,504	7.26	3,250,600	6.80	12,839	6.90	2,906,000	6.08
	>Q3	10,866	5.84	2,390,250	5.00	10,501	5.64	2,401,700	5.02	11,528	6.20	2,346,600	4.91
% of children (6–14 years old) that is not going to school	<Q1	12,574	6.76	2,907,950	6.08	13,112	7.05	3,150,400	6.59	8888	4.78	1,989,200	4.16
	>Q3	9970	5.36	2,167,900	4.53	9508	5.11	2,192,950	4.59	15,073	8.10	3,195,650	6.68
Human Development Index (HDI)	<Q1	12,700	6.83	2,113,750	4.42	11,247	6.04	1,902,800	3.98	19,185	10.31	2,950,200	6.17
	>Q3	7878	4.23	2,539,600	5.31	8230	4.42	2,668,300	5.58	6014	3.23	2,118,250	4.43

Note 1: first quartile (Q1), third quartile (Q3).
Note 2: the percentage of schools was based on the total number of schools (186,080 Brazilian schools), and the percentage of students was based on the total number of students that we estimated (47,813,200 students).

the probability of a school being located in an area with a high amount (in km) of major roadway, and the probability of a school being located in areas with high wildfire occurrence. Using the package "epitools" in R, we estimated the prevalence ratio by unconditional maximum likelihood estimation (Wald), and the 95%CI was calculated using the bootstrap method with 10,000 replicates.

The categories of air pollution exposure (near major roadway, high amount of major roadway, and high wildfire occurrences) were based on the distribution of each air pollution variable. After the spatial matching process between the location of each school and the air pollution data, we classified the schools into four quantiles. Then, for the prevalence ratio estimates, we considered the first quartile for the air

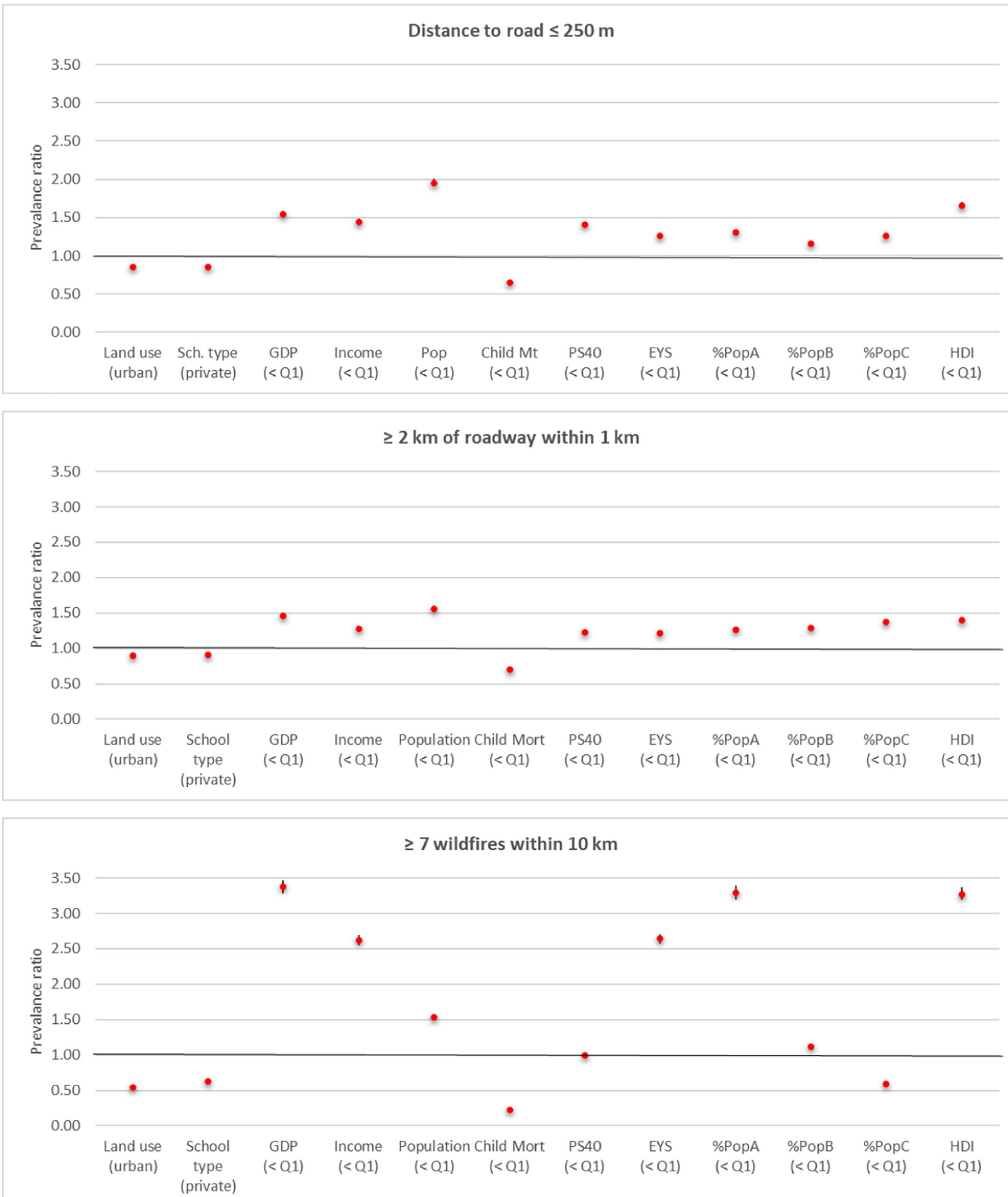


Fig. 1. Prevalence of schools being near a major roadway (≤250 m), in areas with a high amount of major roadway (≥2 km of roadway within a buffer of 1 km), and in areas with high wildfire occurrence (≥7 wildfires within 10 km). Note 1: Gross Domestic Product per capita (GDP), mortality rate of children under the age of five (Child Mort), probability of survival up to at 40 years old (PS40), expected years of schooling (EYS), % of the population in the elementary school and middle school (6–14 years old) that is not over-age (%PopA), % of children (4–5 years old) that is not going to school (%PopB), % of children (6–14 years old) that is not going to school (%PopC), and Human Development Index (HDI). Note 2: quantitative socio-economic factors stratified by the first quartile (Q1). Note 3: rural areas (land use category) and public schools (school type categories) are not shown in the chart because they were defined as the reference for the prevalence ration calculation.

pollution variable distance to road, and the third quartile for the other two air pollution variables, which included distance to major roadway ≤250 m (defined as schools near a major roadway), ≥2 km of roadway within a buffer of 1 km (defined as schools located in areas with a high amount of major roadway), and ≥7 wildfires within 10 km (defined as schools located in areas with high wildfire occurrence).

2.4.2. Spatial patterns of the exposure at the Brazilian schools

We employed the Univariate Local Moran's I approach to assess the spatial patterns of the air pollution exposure over the 186,080 Brazilian schools evaluated in our study. Initially, we generated a spatial weight matrix to represent the spatial constraints parameter. This refers to the conceptualization of spatial relationships (spatial neighboring) among the 186,080 schools. To create this matrix, we chose the k-nearest neighbors algorithm considering the following criteria: Eucledian, as distance method; k nearest neighbors with a minimum of 8 neighbors, as spatial relationships; and no standardization of spatial weights was applied. The spatial weight matrix generated here was used as input data in the Univariate Local Moran's I analysis.

The method Univariate Local Moran's I reflects the goal of targeting specific regions where there are local clusters and local spatial outliers. The approach allows us to provide a classification of schools into four categories related to the spatial association - high-high and low-low spatial clusters, and high-low and low-high spatial outliers. The reference to high and low is relative to the mean of the exposure variable (distance to major roadway, the extent of major roadway, and wildfire). We evaluated cluster/outlier membership likelihood using 999 permutations, with p-value ≤0.05 for the classification of schools into significant spatial clusters and outliers.

3. Results

Table 1 presents a summary of descriptive statistics for the air pollution source emissions data. On average, the 186,080 Brazilian schools assessed in our study are located approximately at 4 km (standard deviation = 21 km) from a nearest major roadway; the average extent of major roadway within a buffer of 1 km around each school was 1.43 km (standard deviation = 1.41 km), and there were on average 6 wildfire records (standard deviation = 10 wildfires) within a buffer of 10 km around the schools.

The number of schools and students by air pollution sources (distance to road ≤250 m, ≥2 km of roadway within a buffer of 1 km, and ≥7 wildfires within a buffer of 10 km) and stratified by socioeconomic parameters is shown in Table 2. Almost ¼ of the Brazilian schools evaluated in our study (24.9%, totaling 44,818 schools) are located within a distance ≤250 m of a major roadway. The majority of the schools closest to major roadways (≤250 m) are public educational institutions, totaling 36,325 public schools. We also observed that most of those schools closest to major roadways are in urban areas (15% of all schools evaluated), in municipalities with low GDP per capita (7%), in regions with low income (6%), in areas with a low population (7%), in municipalities with a high rate of child mortality (7%), in municipalities with a low probability of survival up to 40 years old (7%), in areas with a low probability of expected years of schooling (6.8%), in regions with low % of the population (6–14 years old) in the elementary and middle school that is not over-age (6.8%), in areas with low % of children that are not going to school (6.8%), and in regions with low HDI (6.8%). The results for the exposure variable defined as ≥2 km of roadway within a buffer of 1 km were similar to the results obtained for the distance to road. For wildfire exposure, we estimated that 46,147 Brazilian schools (24.8% of the schools evaluated) were exposed to ≥7 wildfires records within a buffer of 10 km. Over more than 10 million students were at risk of this wildfire exposure. Among those educational institutions, 21% are public schools, 10% are in areas with low GDP per capita, 8% in regions with low income, 6.8% in areas with low population, 10% in municipalities with a high rate of child mortality, 8.8% in areas with a low probability of expected years of schooling, 9.4% in regions with low % of the population (6–14 years old) in the elementary and middle school that is not over-age, and 10% in regions with low HDI (Table 2).

Fig. 1 shows the prevalence of schools being near a major roadway (≤250 m), in areas with a high amount of major roadway (≥2 km of roadway within a buffer of 1 km), and in areas with high wildfire occurrence (≥7 wildfires within 10 km). We estimated that private schools were 15% (95% CI: 13–17%) less likely to be located within 250 m of a major roadway compared with public schools. Schools in municipalities with low GDP, low income, and low populations were associated with a high probability to be near a major roadway. For these economic and demographic factors, we estimated a prevalence ratio of 1.54 (95% CI: 1.50–1.58), 1.44 (95% CI: 1.40–1.48), and 1.95 (95% CI: 1.90–2.00),

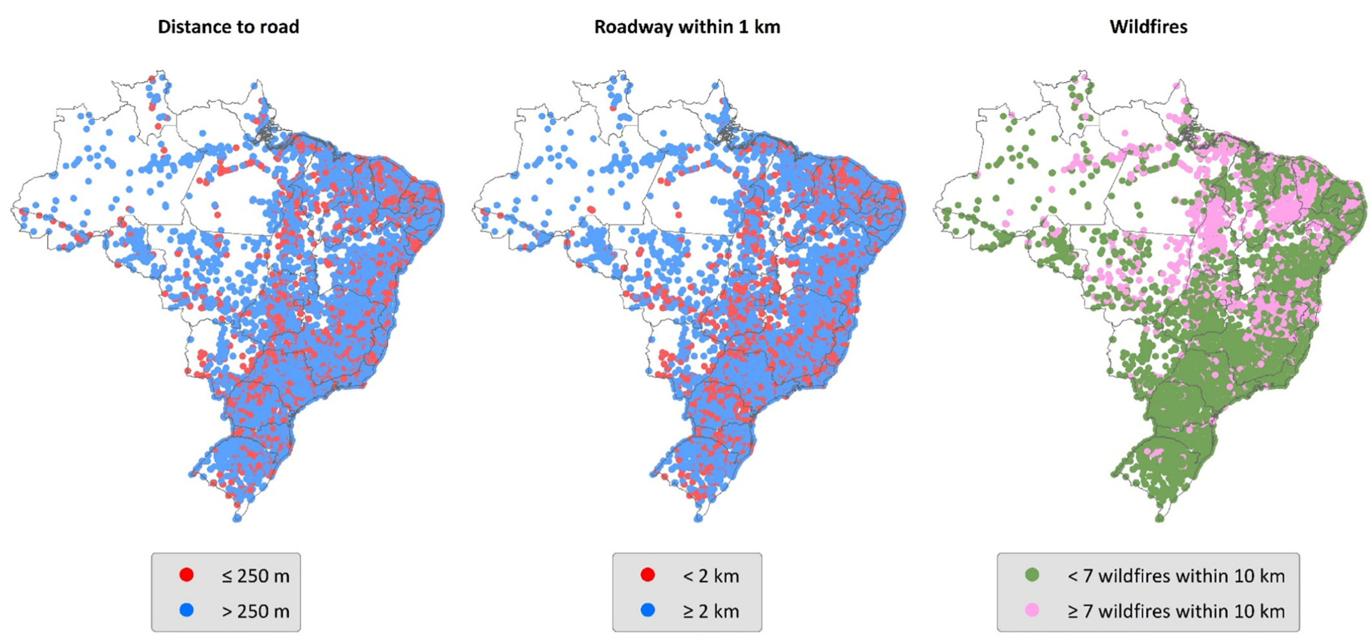
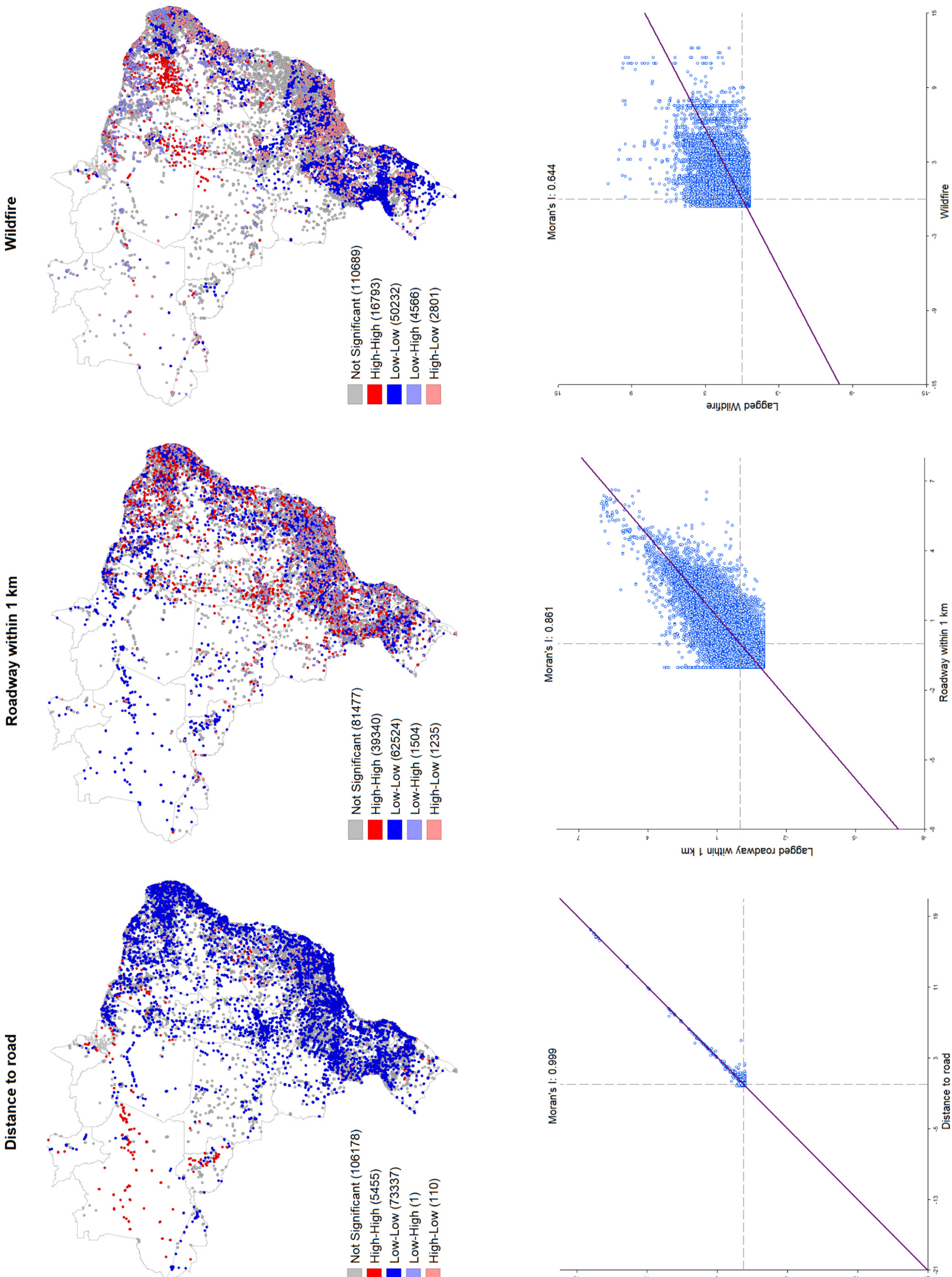


Fig. 2. Spatial distribution of the exposure to each air pollution source categorized by the quartiles defined in this study (first quartile for the air pollution variable distance to road, and the third quartile for the other two air pollution variables, which included distance to major roadway ≤250 m, ≥2 km of roadway within a buffer of 1 km, and ≥7 wildfires within 10 km).


Distance to road
Not Significant (106178)
High-High (5455)
Low-Low (73337)
Low-High (1)
High-Low (110)
Roadway within 1 km
Not Significant (81477)
High-High (39340)
Low-Low (62524)
Low-High (1504)
High-Low (1235)
Wildfire
Not Significant (110689)
High-High (16793)
Low-Low (50232)
Low-High (4566)
High-Low (2801)
Moran's I: 0.999
Lagged distance to road
Distance to road
Moran's I: 0.861
Lagged roadway within 1 km
Roadway within 1 km
Moran's I: 0.644
Lagged Wildfire
Wildfire

respectively. For the health factors, we found associations of schools closest to major roadways in municipalities with high child mortality and low probability of survival up to 40 years old. We estimated that schools in areas with low child mortality were 35% (95% CI: 34–37%) less likely to be within 250 m of a major roadway, and schools in areas with a low probability of survival up to 40 years old were 40% (95% CI: 36–43%) more likely to be within 250 m of a major roadway. For the education factors, we also found associations between schools closest to major roadways and low educational indicators. Our results showed that schools in regions with low expected years of schooling, a low percentage of the population (6–14 years old) that is not overage (older than their grade), a low percentage of children (4–5 years old) that is not going to school, and a low percentage of children (6–14 years old) that is not going to school were 25% (95% CI: 22–28%), 30% (95% CI: 27–22%), 16% (95% CI: 13–18%), and 25% (95% CI: 23–28%) more likely to be located within 250 m of a major roadway, respectively. For HDI, we estimated a probability of 65% (95% CI: 61–69%) of schools with low HDI being near a major roadway. The results (the direction of the probability) for the other exposure variables (≥2 km of roadway within a buffer of 1 km, and ≥7 wildfires within 10 km) were the same as we estimated for the distance to roadway, except for the percentage of children (6–14 years old) that is not going to school. For this educational factor, we estimated that schools closest to roadways were associated with municipalities with a low percentage of children that is not going to school (Fig. 1).

The spatial distribution of exposure to each air pollution source categorized by the quartiles is illustrated in Fig. 2. The results show that the spatial distribution of the Brazilian schools near major roadway (≤250 m) is very similar to schools exposed to a high number of roadways (≥2 km) within a buffer of 1 km. For wildfires, we observed that most of the schools located in areas with high wildfire occurrence (≥7 wildfires within 10 km) are in the North, especially in the Northeast region.

For the spatial pattern analyses, we estimated clusters with low values of the exposure variables for most of the schools (Fig. 3). A total of 73,337; 62,524; 50,232 schools presented low clusters when we assessed the exposure to distance to major roadway, the extent of major roadway within 1 km, and wildfire within 10 km, respectively. Exposure to roadway within 1 km had the highest number of schools with high clusters (39,340 schools), where most of the clusters are in the coastal area in Brazil, the East region. High clusters for distance to road and wildfires were estimated to occur at 5455 and 16,793 schools, respectively (Fig. 3). Our results show that fewest schools were classified as outliers (high-low and low-high spatial outliers) compared to the number of schools classified as clusters (Fig. 3). This relationship between the number of schools classified as clusters and the number of schools classified as outliers is shown in the Moran's scatter plot (corresponding to the location of the points in the four quadrants of the plot) included in Fig. 3. Briefly, the upper right and lower left quadrants suggest a positive autocorrelation (clusters of similar values). In contrast, the lower right and the upper left quadrants suggest a negative spatial autocorrelation (spatial outliers). Also, at the top of each scatter plot in Fig. 3 we show the values of Moran's I, which indicates the slope in the regression of the spatial lag versus the values of each exposure variable.

4. Discussion

Our findings suggest that to assess the influence of air pollution sources on schools the analyses must be assessed beyond the very local level of the schools. About 25% of the Brazilian schools evaluated in our study are located within a distance ≤250 m of a major roadway, have ≥2 km of roadway within a buffer of 1 km, and have ≥7 wildfires records within a buffer of 10 km. Our results indicate significant prevalence ratios of these schools exposed to air pollution sources when we stratified the analyses by socioeconomic factors, including geographic (public schools had an increased likelihood of being exposed), economic (low-income areas had an increased likelihood of being exposed), health (overall, areas with low public health status had an increased likelihood of being exposed), and educational conditions (overall, areas with low educational indicator had an increased likelihood of being exposed). Some of these findings (given that, to our knowledge, some of the exposure source and socio-economic factors considered in our analyses were not evaluated in previous studies, as we described in the introduction) are in agreement with previous investigations that have examined air pollution exposure at schools in other locations. This comparison is detailed below.

A higher proportion of schools in Brazil is located near major roadways compared with American schools. Kingsley et al. (2014) assessed 114,644 US public and private schools and found that 15% of the schools are located within 250 m of a major roadway, impacting about 6.4 million American students. In our study, we estimated that over more than 10 million Brazilian students were likely exposed to traffic emissions due to proximity (≤250 m) of schools to major roadways. Considering the stratification by socio-economic status of the prevalence ratio of schools being within 250 m of a major roadway, our findings are similar to those reported by Kingsley et al. (2014). Both in Brazil (our study) and the US (Kingsley et al.,2014) the exposure to traffic emissions at the schools is disproportionate for lower socio-economic statuses.

In Canada, Amram et al. (2011) assessed 1556 public elementary schools (in Canada's 10 most populous cities) and reported schools in regions with higher median income have a lower likelihood to be near roads (similar to our results) and schools in areas with high population density were more likely to be close to roads (different from our results).

As we mentioned before, we did not find in the literature previous studies that have accounted for wildfire records and length of road within a specific buffer around schools. Therefore, we were unable to perform a direct comparison of our results from these exposure sources with previous investigations. For an inferred comparability purpose, we contrasted these findings with a particular study (Requia et al., 2016) in in the Federal District, Brazil (where Brazil's capital is located) that have estimated the wildfire records and length of road around residences. We assume here that many students live close to their schools and so these exposure metrics may be similar at home and at schools. Requia et al. (2016) estimated that on average, there are about 3.4 km of major roadways within a buffer of 1 km around homes in the Federal District. For the residences with 3.4 km of roads (at the buffer 1 km) the authors found an increase of 15 hospital admissions due to cardiorespiratory diseases. For wildfire, Requia et al. (2016) reported an average of 7 wildfire records within a buffer of 2.5 km (this was the maximum buffer considered by the authors). At 1 km of buffer, with an average of 2 wildfires, they estimated a risk of 4 hospital admissions.

For the analysis of the spatial patterns, our results show that a substantial number of schools (42, 54, and 36% when we accounted for the exposure variables distance to road, roadway within 1 km, and wildfire, respectively) has a positive autocorrelation, suggesting that exposure level at these schools are similar to their neighbors. Only a small proportion of schools (0.05, 1.47, and 3.95% respectively for the exposure variables distance to road, roadway within 1 km, and wildfire,

Fig. 3. Spatial patterns of the exposure at the Brazilian schools – results from the method Univariate Local Moran's I. Note 1: clusters with high values (high-high), clusters with low values (low-low), outliers with high values (high-low), outliers with low values (low-high). Note 2: Moran scatter plots are shown in the bottom part. These scatter plots provide a classification of spatial association into four categories (high-high, low-low, low-high and high-low, relative to the mean), corresponding to the location of the points in the four quadrants of the plot. The upper right quadrant indicates the high-high clusters, upper left quadrant indicates low-high outliers, the bottom right quadrant indicates the high-low outliers, and the bottom left quadrant indicates the low-low clusters.

respectively) presented a negative spatial autocorrelation, indicating spatial outliers and that their exposure levels are different from their neighbors. An advantage of this spatial analysis is that we can identify the schools classified as positive or negative autocorrelation. This allows policymakers to create effective decisions at the local and regional scales, given the possibility to recognize regions with similar or dissimilar levels of exposure at the schools.

Most of the previous investigations on the school's exposure to air pollution sources have considered only distance to road as a proxy of air pollution sources. In our study, we added length of road within a specific buffer, which may be a different metric of air pollution, allowing us to compare the results with the most used metric in the literature - distance to road. In our analyses, we observed similar results for both metrics - distance to road and length of roads within a buffer, indicating some consistency in the measurement of these exposure variables across the Brazilian schools.

Note that these indicators related to roadways are surrogates for air pollution exposure. For example, NO_2 is a gaseous pollutant mainly formed in the atmosphere from of NO and O_3. Direct emissions of NO_2 can occur from fossil fuel combustion. In urban environments, traffic-related combustion, especially diesel fueled vehicle, contributes substantially to ambient NO_2 concentration (Lamsal et al., 2013). In urban areas, both anthropogenic and natural NO_x and VOC are important precursors of O_3 formation. In contrast, in non-urban areas, the biogenic VOC emitted from vegetation is the most important precursor of O_3 formation. The intra-urban variations of O_3 levels are also linked to the geographic variation of sources of O_3 precursors and sources of oxidizing compounds such as road traffic-related NO_x (Coelho et al., 2014; Huo et al., 2009). For $PM_{2.5}$, although important faction of particulate matter attributable to roadways is secondary, studies show that the total (primary and secondary particulate matter) motor-vehicle-related emissions are considered a significant source of air pollution. For example, traffic emissions are responsible for 30% of $PM_{2.5}$ in Toronto, Canada (Brook et al., 2007), 22% of $PM_{2.5}$ in Boston, United States (Masri et al., 2015), 25% of PM_{10} and 30% of $PM_{2.5}$ in five Chilean metropolitan regions (Kavouras et al., 2001).

Our study has some limitations, mostly, misclassification error. First, the number of students was estimated based on a categorical variable included in the dataset, this generates some classification error. Second, we estimated the long-term exposure based only on the spatial analysis

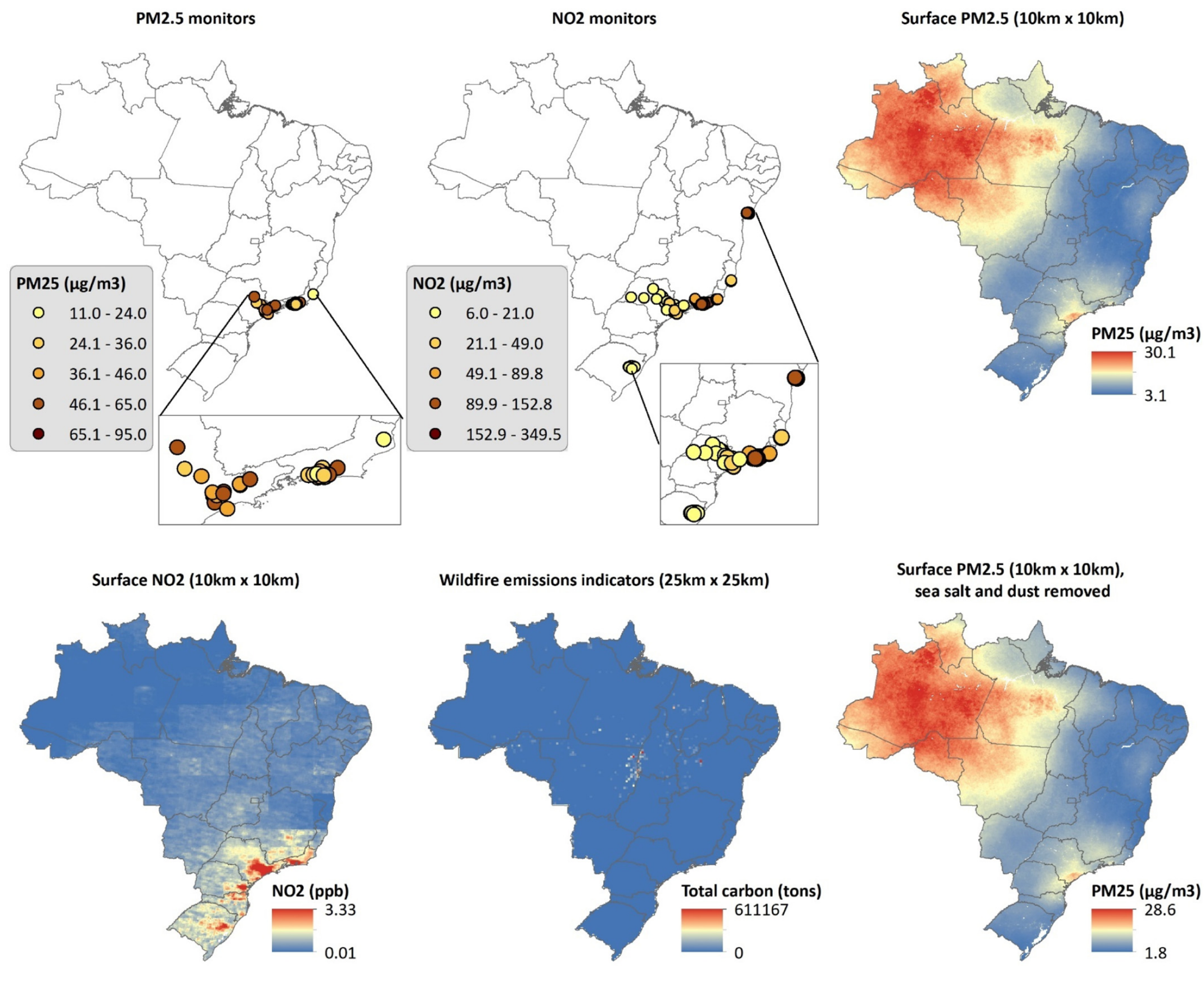


Fig. 4. Air pollution in Brazil: air pollution stations where $PM_{2.5}$ and NO_2 were measured in 2016, annual mean ambient concentration of $PM_{2.5}$ at 10 km × 10 km spatial resolution for the year 2016 (derived from satellite remote sensing observations), annual mean ambient concentration of NO_2 at 10 km × 10 km for the year 2012 (derived from satellite remote sensing observations), annual mean wildfire emission indicator at 25 km × 295 km for the year 2016 (derived from satellite remote sensing observations), and annual mean ambient concentration of $PM_{2.5}$ with sea salt and dust removed at 10 km × 10 km for the year 2016 (derived from satellite remote sensing observations).

(distance and buffer analyses) for the location of the schools and the exposure sources, which may also generate misclassification. Actual exposure depends on numerous geographical factors (e.g., topography, meteorological conditions, land use), transportation (e.g., type of vehicles, transportation fleet, emission rates), and time-activity patterns (e.g., time spent indoor and outdoor environment, exchange rates, infiltration) that represent the student exposure over the seasons (Carrion-Matta et al., 2019). Also, socio-economic factors used for stratification are at the municipality level, and not at the school level. Finally, given that air pollution is the key consideration point by this study, would be important to compare the air quality situation in Brazil (e.g., the spatial distribution of the background annual concentrations of $PM_{2.5}$ or NO_2) with the different clusters of schools. However, we were unable to perform this analysis since Brazil has a limited number of air pollution monitoring stations. There is a total of 5570 municipalities in Brazil, but only 1.7% of them have an air pollution monitoring network. Nationally, there are 252 monitoring stations, but not every station monitors all important pollutants such as $PM_{2.5}$, NO_2, and O_3. Also, more than 50% of these stations are located only in two Brazilian states – São Paulo and Rio de Janeiro (Brazil has 26 states + the Federal District). We show in Fig. 4 two maps illustrating the spatial distribution of the limited number of air pollution stations in Brazil where $PM_{2.5}$ and NO_2 were measured in 2016. In order to address this limitation related to the spatial covering of air pollution levels, we also show in Fig. 4 the gridded ambient air pollution concentrations inferred from satellite observations, including the annual mean ambient concentration of $PM_{2.5}$ at 10 km × 10 km spatial resolution for the year 2016 (data downloaded from https://sedac.ciesin.columbia.edu/data/), annual mean ambient concentration of NO_2 at 10 km × 10 km for the year 2012 (data downloaded from https://sedac.ciesin.columbia.edu/data/), annual mean wildfire emission indicator at 25 km × 25 km for the year 2016 (data downloaded from https://sedac.ciesin.columbia.edu/data/), and annual mean ambient concentration of $PM_{2.5}$ with sea salt and dust removed at 10 km × 10 km for the year 2016 (data downloaded from http://fizz.phys.dal.ca/~atmos/martin/?page_id=140). The maps shown in Fig. 4 may help understanding the importance of this study by comparing the air quality situation in Brazil with different level of school's exposure to air pollution sources, including roadways and wildfires (Figs. 3 and 2). For example, looking at the maps showing the surface $PM_{2.5}$ (Fig. 4, top right) and the surface $PM_{2.5}$ with sea salt and dust removed (Fig. 4, bottom right) we see that in Brazil anthropogenic $PM_{2.5}$ pollution is significant. According to previous studies, traffic emission and wildfire emissions are the main anthropogenic sources in Brazil (Réquia et al., 2016; Silva et al., 2016).

5. Conclusions

To our knowledge, this is the first study that estimates exposure to air pollution sources at more than 180 thousand schools in Brazil, accounting for three proxies of air pollution source emissions, and assessing the variation of the exposure levels by 12 socio-economic factors. Our results showed significant variation of exposure over the Brazilian schools, and by the socio-economic factors. This demonstrates that efforts to reduce and control air pollution emissions need to be applied according to the characteristics of each area.

A large body of literature has showing that living, working, and studying near roads and wildfires may involve many potentially hazardous conditions for human health, including the increased risk of certain diseases that are associated with the learning process – e.g., neurobehavioral function (Wang et al., 2009) and cognitive deficits (Calderón-Garcidueñas et al., 2008; Suglia et al., 2008). In our study, we evaluated the exposure for more than 40 million students who attended Brazilian schools in 2015, and from those, approximately 10 million were likely to be exposed to high levels of air pollution from traffic and wildfire. Our findings can be incorporated in future public policies to develop effective environmental, transportation, educational, and urban planning interventions that may protect those Brazilian students from exposure to environmental hazards and improve their safety, health, and learning performance.

CRediT authorship contribution statement

Weeberb J. Requia: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft. **Henrique L. Roig:** Writing - review & editing. **Joel D. Schwartz:** Writing - review & editing.

Declaration of competing interest

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.

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