Disparities in Air Pollutants Across Racial, Ethnic, and Poverty Groups at US Public Schools

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Abstract We investigate socioeconomic disparities in air quality at public schools in the contiguous US using high resolution estimates of fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) concentrations. We find that schools with higher proportions of people of color (POC) and students eligible for the federal free or reduced lunch program, a proxy for poverty level, are associated with higher pollutant concentrations. For example, we find that the median annual NO_2 concentration for White students, nationally, was 7.7 ppbv, compared to 9.2 ppbv for Black and African American students. Statewide and regional disparities in pollutant concentrations across racial, ethnic, and poverty groups are consistent with nationwide results, where elevated NO_2 concentrations were associated with schools with higher proportions of POC and higher levels of poverty. Similar, though smaller, differences were found in $PM_{2.5}$ across racial and ethnic groups in most states. Racial, ethnic, and economic segregation across the rural-urban divide is likely an important factor in pollution disparities at US public schools. We identify distinct regional patterns of disparities, highlighting differences between California, New York, and Florida. Finally, we highlight that disparities exist not only across urban and non-urban lines but also within urban environments.

Plain Language Summary We find that, nationally, US public schools with higher proportions of impoverished and racially/ethnically marginalized students are associated with higher average concentrations of two types of air pollutants, particulate matter and nitrogen dioxide (NO_2), relative to schools with lower proportions of marginalized students. Disparities in pollutant concentrations are also more pronounced in some regions of the US where marginalized students are concentrated in urban areas and non-marginalized students are concentrated in rural areas, such as the state of New York. We find that larger relative disparities exist for NO_2 compared to particulate matter, but qualitative results are similar.

1. Introduction

Air pollution poses significant health and economic burdens worldwide (Cohen et al., 2017; World Health Organization, 2013). Both fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) have garnered significant research attention due to the adverse health outcomes associated with exposure. Exposure to $PM_{2.5}$, which has a variety of natural and anthropogenic sources, is considered the greatest environmental risk factor for premature death worldwide (Cohen et al., 2017; World Health Organization, 2013). NO_2, a toxic gas and component of nitrogen oxides (NO_x), is primarily derived from combustion. Strong associations have been found between $PM_{2.5}$ pollution and cardiopulmonary and neurodegenerative diseases, lung cancer, and all-cause mortality (e.g., Atkinson et al., 2018; Cohen et al., 2017; Faustini et al., 2014; Hoek et al., 2013; Kioumourtzoglou et al., 2016; Shi et al., 2020; World Health Organization, 2013) and between NO_2 pollution and respiratory effects (EPA, 2016), including pediatric asthma development (Khreis et al., 2017).

Air pollution impacts people of all ages, but can be especially hazardous to children. Children are at greater risk of adverse health effects from air pollution exposure due to postnatal and early childhood organ development (Brockmeyer & D'Angiulli, 2016; Gehring et al., 2013; Kulkarni & Grigg, 2008); increased pollutant intake to body mass ratios (Brockmeyer & D'Angiulli, 2016); and increased time spent outdoors compared to

adults (Bateson & Schwartz, 2008). Exposure to high concentrations of air pollutants during childhood has been linked to increased risk for developing or exacerbating respiratory diseases such as asthma and chronic obstructive pulmonary disease (Chatkin et al., 2021; Han et al., 2021; Jerrett et al., 2008; Madureira et al., 2015; van Zoest et al., 2020), as well as reduced lung function (Gehring et al., 2013). Importantly, decreases in $PM_{2.5}$ and NO_2 concentrations are associated with improvements in children's lung function. Studies have also found links between children's exposure to air pollution and diminished cognitive function, lower intelligence quotient scores (Mohai et al., 2011; Sunyer, 2008), and mental health problems such as attention deficit/hyperactivity disorder, anxiety, and depression (Myhre et al., 2018; Roberts et al., 2019).

Many factors govern a child's exposure to air pollution, but the location and type of school where each child attends is an important factor (e.g., Mohai et al., 2011). Over 54 million children attend US public and private schools (National Center for Education Statistics, 2021). These children spend an average of 6.64 hr a day in school for 180 days a year (i.e., 1,200 hr per year) (National Center for Education Statistics, 2008). While at school, students spend time in outdoor environments during activities like recess, physical education class, free time between class, and extracurricular activities. Outdoor air pollutants can also infiltrate indoors (e.g., Habre et al., 2014; Reche et al., 2015; Wichmann et al., 2010). Schools are often in proximity to heavily trafficked roads and commercial areas (Appatova et al., 2008; Hauptman et al., 2020; Kweon et al., 2018; Shoari et al., 2022). Poor air quality near schools has been linked to lower student test scores, grade point averages, and attention retention (Grineski et al., 2020; Mohai et al., 2011; Sunyer, 2008). Additionally, poor air quality at schools has been associated with chronic absenteeism (MacNaughton et al., 2017), which is linked to poorer academic performance from kindergarten through 12th grade (Ready, 2010). Despite evidence of high pollutant exposures at US schools, there are currently no mandatory federal guidelines or agencies in place that protect students from attending schools in polluted areas (Sampson, 2012).

The burden of air pollution disproportionately affects marginalized communities, both in terms of wealth and race/ethnicity. Past analyses have shown disparities between race, ethnicity, and socioeconomic groups in modeled or measured ambient concentrations (Colmer et al., 2020; Gray et al., 2013; Hajat et al., 2015; Liu et al., 2021; Mohai, Pellow, et al., 2009) or disparities in proximity to heavy pollution sources such as roadways and industrial sources (Brender et al., 2011; Mohai, Lantz, et al., 2009; Mohai, Pellow, et al., 2009). Estimates of $PM_{2.5}$ disparities across racial, ethic, and poverty groups have shown that, in the US, $PM_{2.5}$ pollution is disproportionately generated from the majority population but disproportionately breathed in by the minority population (Tessum et al., 2019). Furthermore, the sources of these $PM_{2.5}$ disparities are likely widespread across all emission sectors including industrial emissions, light and heavy-duty vehicles, and construction; and they exist across many spatial/governmental scales (e.g., local, state, and federal) (Tessum et al., 2021).

School children in the US are also impacted by the racial, ethnic, and economic disparities in air pollutants. Although few studies have investigated pollution disparities at schools across the US nationally, previous studies of specific school districts have found that modeled average pollutant concentrations are higher at schools that have higher percentages of Black or African American, Hispanic, and multi-ethnic students (Morello-Frosch et al., 2002). Additionally, these schools are in closer proximity to pollution sources (Chakraborty & Zandbergen, 2007; Green et al., 2004; Maantay, 2002). Schools with a higher percentage of students eligible for the federal Free and Reduced Price Lunch program, which is often used as a proxy for poverty in schools, have also been found to be located nearer to $PM_{2.5}$ emission sources such as heavy road traffic (Gaffron & Niemeier, 2015). Recently, the first nationwide study on air pollution disparities between schools, specifically on airborne neurotoxins (not $PM_{2.5}$ or NO_2), found that students who identified as Hispanic, Black or African American, Asian or Asian/Pacific Islander, and those eligible for free or reduced meals were more likely to attend schools with higher average concentrations of airborne neurotoxins (Grineski & Collins, 2018).

A nationwide analysis of disparities in US public schools has not been conducted for either $PM_{2.5}$ or NO_2, two criteria pollutants. Since the mental and physical impacts of exposure to these pollutants at schools can have lifelong effects on children's success and well-being, understanding where disparities exist can help inform air pollution mitigation strategies that benefit children. To investigate air pollution disparities across racial, ethnic, poverty, and locale (e.g., urban and rural) groups at US public schools, we use gridded, high-resolution concentration data sets for $PM_{2.5}$ (Hammer et al., 2020; van Donkelaar et al., 2019, 2021) and NO_2 (Anenberg et al., 2022; Cooper et al., 2020) along with data on students at public schools.

Table 1
Counts of Students Belonging to Different Racial, Ethnic, Poverty, and Urbanicity From the NCES Data Set

Category	Number of students
Total number in CONUS	49,528,556
Racial/ethnic demographics	
White	23,010,769 (46.5%)
Hispanic	13,766,440 (27.8%)
Black or African American	7,472,589 (15.1%)
Asian or Asian/Pacific Islander	2,611,033 (5.3%)
American Indian/Alaska Native	429,722 (0.9%)
Native Hawaiian/Other Pacific Islander	129,881 (0.3%)
Two or more races	2,106,522 (4.3%)
Poverty indicators	
Eligible for free or reduced lunch program	23,880,131 (48.2%)
Locale categorization	
Urban	15,198,470 (30.7%)
Suburban	19,486,154 (39.3%)
Town	5,325,761 (10.8%)
Rural	9,518,171 (19.2%)

Note. The percentages of students in each demographic relative to the total number of students are in parentheses.

2. Materials and Methods

2.1. National Center for Education Statistics Data

We retrieved general information, demographics, and financial information for 98,537 public schools (pre-kindergarten through 12th grade) for the contiguous United States (CONUS) from the National Center for Education Statistics (NCES) for 2019. The NCES data set can be found and indexed using the Elementary/Secondary Information System table generator tool (https://nces.ed.gov/ccd/elsi/tableGenerator.aspx). We retrieved enrollment details from the NCES data set such as student counts of various racial and ethnic demographics (White, Hispanic, Black or African American, American Indian/Alaska Native, Native Hawaiian or other Pacific Islander, and two or more races). We use the terminology used in the NCES data set for consistency. We use the term people of color (POC) in our results to describe all students who did not identify as White. We are not able to distinguish between students who identified as White and non-Hispanic versus White and Hispanic, so we include all people who identify as Hispanic in the POC category. We calculate the fraction of POC students in each school by finding the complement of the fraction of students who identified as White.

We use the fraction of students eligible for free or reduced lunch as a proxy for poverty levels in schools since student families must be at or below 185% of the federal poverty line to qualify. This proxy has been used in previous research (e.g., Grineski & Collins, 2018; Mohai et al., 2011; Morello-Frosch et al., 2002; Pastor et al., 2006). However, it is not a perfect measure of poverty (National Center for Education Statistics, 2015), because eligibility in the US is based on poverty levels set at the federal level, without consideration of regional living costs. The NCES also categorizes school locales as city (defined here as urban), suburban, town, or rural. A detailed description of how we filter schools based on school size, data availability, and data quality can be found in Text S1 in Supporting Information S1. The number of students that belong to each racial, ethnic, poverty, and locale category, using the enrollment details reported in the NCES data set, are shown in Table 1. Heat density maps of student counts for various racial/ethnic demographics are also shown in Figures S1–S5 in Supporting Information S1.

2.2. Estimates of Fine Particulate Matter ($PM_{2.5}$) and Nitrogen Dioxide (NO_2)

To study disparities in particulate matter across US public schools, we used the annual average of a $PM_{2.5}$ concentration data set that combines satellite retrievals, chemical transport modeling and ground-based observations (V5. GL.02; van Donkelaar et al., 2021; made available by the Washington University in St. Louis (WUSTL, 2022b)). This data set combines multiple National Aeronautics and Space Administration aerosol optical depth products (Sea-viewing Wide Field-of-view Sensor/MODerate Resolution Imaging Spectrometer [MODIS] Deep Blue, MODIS Dark Target, MODIS Multi-Angle Implementation of Atmospheric Correction, and Multi-angle Imaging SpectroRadiometer) with the Goddard Earth Observing System chemical transport model to produce geophysical estimates of surface $PM_{2.5}$ concentrations (Figure S6 in Supporting Information S1) which are then calibrated to ground-based observations using a geographically weighted regression. Data are provided at the resolution of the finest included data sources (0.01° × 0.01°; ~1.1 km) to preserve information, although $PM_{2.5}$ gradients at this resolution are not expected to be fully resolved due to the influence of coarser resolution inputs (van Donkelaar et al., 2021). We averaged 3 years (2017–2019) of $PM_{2.5}$ estimates over CONUS for this study. School location concentrations were assigned based on the nearest grid cell center.

We used two annual average NO_2 data sets over CONUS for our analysis including those developed by Anenberg et al. (2022) and Cooper et al. (2020). The Anenberg et al. (2022) NO_2 data set (available at Mohegh and Anenberg (2021)) contains annually averaged NO_2 estimates at a 1-km resolution from 1990 to 2019 (Figure S7 in Supporting Information S1). The NO_2 estimates were created using a combination of land-use regression (LUR) model predictions and column density NO_2 observations from the Ozone Monitoring Instrument satellite

sensor. The Cooper et al. (2020) data set (available at WUSTL (2022a)) used a chemical transport model in combination with satellite observations from the TROPOspheric Monitoring Instrument satellite (Figure S8 in Supporting Information S1). We show results from the Anenberg et al. (2022) data set in Section 3 since this data set was at a higher resolution (1 km) than Cooper et al. (2020) (∼2.8 km). Also, the use of a LUR model allowed Anenberg et al. (2022) to explicitly incorporate traffic data for the NO_2 estimates. The reliance on traffic data is important in our analysis since previous studies have shown that schools with higher poverty levels also tended to be closer to major roadways (Amram et al., 2011; Green et al., 2004). We present results using the Cooper et al. (2020) data set as a sensitivity analysis in Supporting Information S1. We averaged 3 years (2017–2019) of NO_2 estimates from the Anenberg et al. (2022) data set but only used 2019 (the only year available) from the Cooper et al. (2020) data set. We co-located each school to the nearest gridcell center in each data set.

2.3. Analysis and Statistical Approach

In Section 3.1, we calculated the complementary cumulative distribution functions of NO_2 and $PM_{2.5}$ exposure at schools for various demographics by weighting the ambient concentrations at each school by the number of students in each demographic. To do this, we assigned NO_2 and $PM_{2.5}$ values to every student in CONUS based on the concentration at the school they attended. We then grouped the students by racial, ethnic, and poverty demographics, and calculated the percentage of students in each demographic who attended schools above a given pollutant concentration. In Sections 3.2 and 3.3, we compared the distributions of NO_2 and $PM_{2.5}$ concentrations assigned to schools that have been grouped by the percentages of various racial, ethnic, and poverty demographics (e.g., schools with greater than 60% of students that identify as White), as well as various locale categories (e.g., urban and rural). Note that some states such as Oklahoma and West Virginia are not present in our analysis of disparities across poverty groups because the counts of students eligible for free or reduced meals were not available in the NCES data set.

To assess the statistical significance of the differences in these distributions, we employed a two-sided Mann-Whitney U test (Mann & Whitney, 1947) that estimates the probability that two sample groups were randomly selected from the same parent distribution without assuming a distribution shape. We reported the p-values for each comparison in Supporting Information S1 and assumed two distributions were significantly different if the p-value was less than 0.05.

3. Results

3.1. National Results

Figure 1a contains the complementary cumulative distribution functions of NO_2 for students in CONUS public schools from each NCES racial/ethnic demographic category (except those who identify as Native Hawaiian/Other Pacific Islander or 2 or more races). The exposure disparity, using White students as the reference group, can be expressed as the horizontal distance between two complementary cumulative distribution curves, evaluated at a given quantile (parentage of student demographic in Figure 1). We calculate disparities at the median and 90th percentile, representing typical and high-exposure scenarios, respectively. We find that, nationally, using the Anenberg et al. (2022) NO_2 data set and comparing concentrations weighted by the number of students in each demographic at each school, White students attend schools with the lowest concentrations of NO_2 (median: 7.7 ppbv; 90th percentile: 11.6 ppbv), followed closely by American Indian/Alaska Native students (median: 8.1 ppbv; 90th percentile: 12.6 ppbv). Conversely, students from other marginalized groups–including Black or African Americans (median: 9.2 ppbv; 90th percentile: 14.9 ppbv), Asian or Asian/Pacific Islanders (median: 9.7 ppbv; 90th percentile: 14.7 ppbv), and Hispanics (median: 9.9 ppbv; 90th percentile: 15.0 ppbv)—attend schools with relatively higher concentrations of NO_2. When repeating the analysis using the Cooper et al. (2020) data set, we also find that White and American Indian/Alaska Native students attend schools with lower concentrations, on average, relative to the other racial/ethnic groups (Figure S9 in Supporting Information S1). However, the overall concentrations using the Cooper et al. (2020) data set are lower for all demographic categories (i.e., less than 40% of students of any racial/ethnic group attended schools above 5 ppbv).

Figure 1b contains the complementary cumulative distribution functions of $PM_{2.5}$ for students in CONUS public schools. The $PM_{2.5}$ curve is steeper than NO_2, indicating a narrower exposure distribution: ∼36% of CONUS students from all racial/ethnic groups attend schools above 8 μg m^{-3}, whereas only ∼7% attend schools above
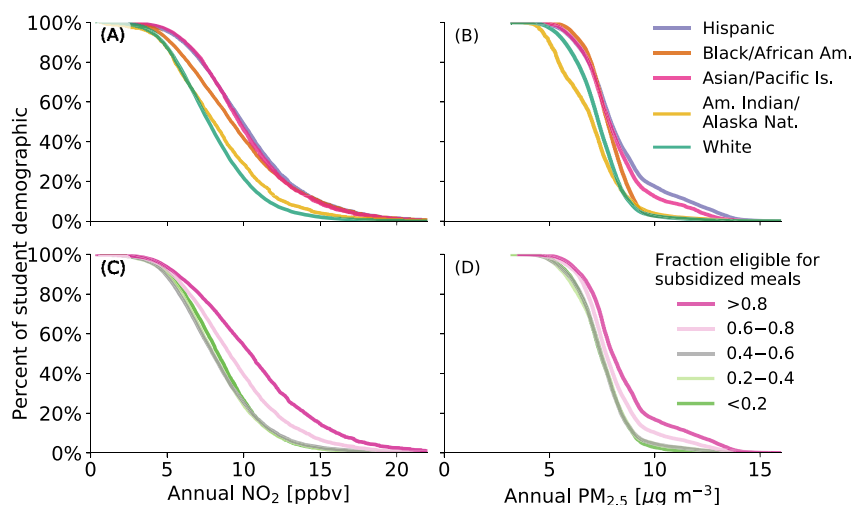
Figure 1. Complementary cumulative distribution functions of annually averaged NO$_2$ (a) and PM$_{2.5}$ (b) at schools for students that belong to specific racial/ethnic demographics. Complementary cumulative distribution functions of annually averaged NO$_2$ (c) and PM$_{2.5}$ (d) at schools of differing poverty levels, measured by the fraction of students eligible for free or reduced meals at each school. Each plot shows the percentage of the students that attend schools where the co-located annually averaged mean of each pollutant is above a given concentration.

10 µg m^{-3}. The disparities in PM$_{2.5}$ exposure are similar to NO$_2$, though the relative magnitudes are smaller. For example, the distribution of PM$_{2.5}$ concentrations are lowest for White (median: 7.3 µg m^{-3}; 90th percentile: 8.8 µg m^{-3}) and American Indian/Alaska Native students (median: 7.0 µg m^{-3}; 90th percentile: 8.9 µg m^{-3}). Students from ethnically and racially marginalized groups such as Black or African American (median: 7.7 µg m^{-3}; 90th percentile: 9.0 µg m^{-3}), Asian or Asian/Pacific Islander (median: 7.8 µg m^{-3}; 90th percentile: 10.5 µg m^{-3}), and Hispanic students (median: 7.9 µg m^{-3}; 90th percentile: 11.6 µg m^{-3}) attend schools with higher distributions of ambient PM$_{2.5}$ concentrations.

A higher proportion (~40%) of Black or African American students attend schools with PM$_{2.5}$ above 8 µg m^{-3}, relative to White or American Indian/Alaska Native students (23%–27%). However, these demographics all have similarly low proportions of students attending schools with concentrations above 10 µg m^{-3} (2%–4%), compared to Asian/Pacific Islander or Hispanic students (12%–17%). The steep drop-off in concentrations for Black and African American students occurs because there are more Black and African American students in the rural and suburban South, and less in the central valley of California (Figure S2 in Supporting Information S1), which is the region with the highest concentrations of annually averaged PM$_{2.5}$ in CONUS from the V5.GL.02 data set (Figure S6 in Supporting Information S1). Thus, relative to Hispanic and Asian or Asian/Pacific Islander students, who are heavily concentrated in the central valley of California (Figures S3 and S4 in Supporting Information S1), a small proportion of Black or African American students attend schools with concentrations above 10 µg m^{-3}.

We also compared the NO$_2$ and PM$_{2.5}$ concentrations at schools based on indicators for poverty level. We calculate the complementary cumulative distribution functions of NO$_2$ (Figure 1c) and PM$_{2.5}$ (Figure 1d) concentrations for students, where students are grouped by the fraction of students eligible for subsidized meals at the schools that each student attends. We find that students attending schools with low-to-moderate poverty levels (fraction of students eligible for subsidized meals <0.6) have similar distributions of NO$_2$ (medians: 8.0–8.3 ppbv; 90th percentiles: 11.9–12.1 ppbv) and PM$_{2.5}$ (medians: 7.4–7.5 µg m^{-3}; 90th percentiles: 9.0 µg m^{-3}). Higher poverty levels in schools are associated with increased concentration levels. The highest concentrations of NO$_2$ (median: 10.5 ppbv; 90th percentile: 16.2 ppbv) and PM$_{2.5}$ (median: 8.0 µg m^{-3}; 90th percentiles: 11.7 µg m^{-3}) are at schools with greater than 80% of students eligible for subsidized meals. We find similar results when we repeat this analysis using the Cooper et al. (2020) data set (Figure S9 in Supporting Information S1), though the distributions of NO$_2$ for low and high poverty groups are more similar at low-to-moderate concentrations, likely because both groups are concentrated around urban areas such as Chicago, New York, and Los Angeles.

In Figure 2, we investigate the intersection of race, ethnicity, poverty, and pollutant concentrations for NO$_2$ and PM$_{2.5}$ around CONUS public schools for different locale categories. When interpreting the results in Figure 2,
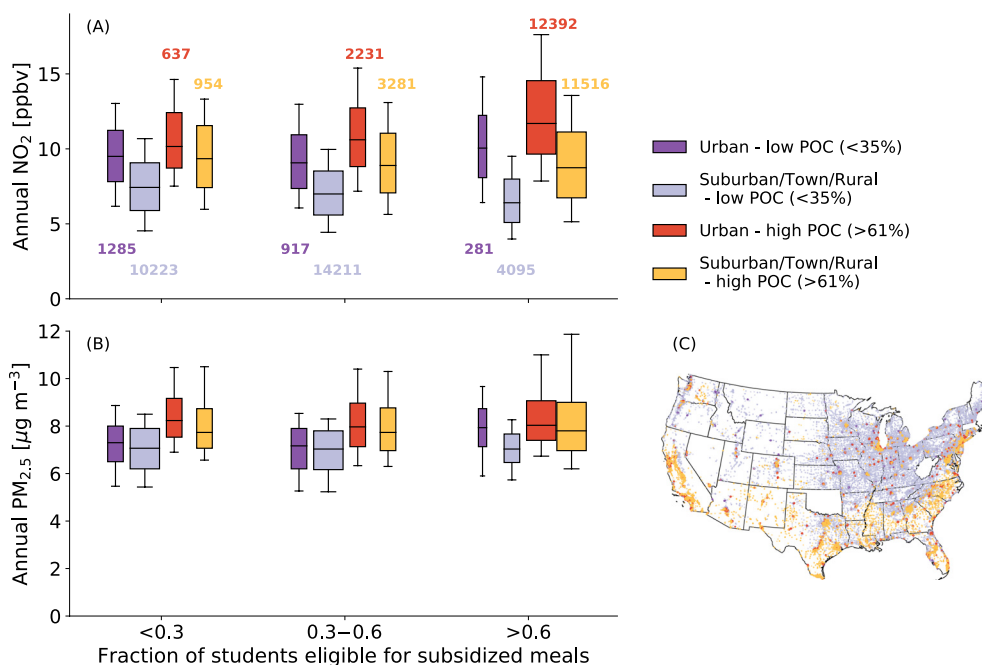
Figure 2. Boxplots of annually averaged (a) NO_2 and (b) $PM_{2.5}$ surface mixing ratios split into categories of poverty level, which is defined by the fraction of students eligible for free or reduced lunch. A greater fraction of free or reduced lunch indicates a higher level of poverty. Within each poverty-level bin, separate boxplots are shown for schools in urban and combined suburban, town, and rural locations for low people of color (POC) schools (<35% POC students) and high POC schools (>61% POC students). The thresholds for high and low POC schools are based on the 60th and 40th percentile of the percentage of POC students in all public schools across the contiguous US. The width of each boxplot is scaled for visual aid to three size categories corresponding to the number of schools in each distribution, which are listed near each distribution in corresponding colors. (c) A map of schools that belong in each race and locale category.

it is important to note that the demographics, poverty levels, and locale categories of each school are often inter-related. For example, schools with more than 61% POC students (hereafter referred to as "high POC schools"; based on the 60th percentile nationwide) also tend to have higher levels of poverty and be located in urban areas across the US (the number of schools in each category is depicted by box widths), as well as in suburban, town, and rural areas in the southeastern US, Texas, and California (Figure 2c). In contrast, schools with less than 35% POC students (hereafter referred to as "low POC schools"; based on the 40th percentile nationwide) tend to have lower levels of poverty and be located in suburban, town, and rural areas, especially in the northeastern and midwestern US (Figure 2c).

We find in Figure 2a that, nationally, high POC schools tend to have higher 25th, 50th, and 75th percentiles of NO_2 concentrations compared to low POC schools. For example, at the urban schools with the highest poverty levels, the median ambient NO_2 at high POC schools was approximately 1.6 ppbv higher than low POC schools. Similarly, at suburban, town, and rural schools, the median NO_2 concentrations were approximately 2.3 ppbv higher at high POC schools compared to low POC schools. We also see in Figure 2a, that urban schools were associated with higher NO_2 concentrations compared to suburban, town, and rural schools in the US, which is unsurprising given the sources of NO_2 pollution.

We find disparities in ambient NO_2 concentrations across poverty levels nationally, but the relationship also depends on the locale category. For example, results in Figure 2a suggest that urban schools with higher poverty levels have higher NO_2 concentrations compared to urban schools with lower poverty levels. For suburban, town, and rural schools, however, there is little distinction or perhaps even small decreases in NO_2 concentration based on poverty level (again, as indicated by fraction of students eligible for free or reduced lunch). When we separate suburban schools from those in town and rural areas, we find that NO_2 concentrations at suburban schools also increase with increasing poverty levels for high POC schools but stay the same for low POC schools (Figure S10a in Supporting Information S1). Additionally, NO_2 concentrations around schools in town and rural areas generally decrease with increasing poverty level (Figure S10a in Supporting Information S1). Thus, generally, the

poorest urban schools had the highest distribution of NO_2 concentrations, while the poorest rural schools had the lowest distribution of NO_2 concentrations. The low NO_2 concentrations in these rural areas with higher poverty levels could be indicative of a lack of industry and development.

As NO_2 concentrations are higher in urban areas, using these locale categories can further highlight disparities in ambient NO_2 concentrations across poverty levels and racial/ethnic groups. For example, when we compare the median NO_2 concentration of high POC, urban, high-poverty schools against low POC, suburban, town, and rural, moderate-poverty schools, we find a disparity of approximately 4.3 ppbv (urban high-poverty schools ∼50% higher) and even larger disparities in the tails of the distributions.

When we compare the medians of each distribution in Figure 2a using two-sided Mann-Whitney U tests, we find that almost all of the distributions are different to an acceptable statistical significance ($p < 0.05$) (Figure S11a in Supporting Information S1). The only distributions that are not significantly different from each other are when low POC urban schools are compared to high POC suburban schools in low and medium poverty-level categories (Figure S11a in Supporting Information S1).

To note, we repeat this analysis using various percentiles of POC students in schools nationwide as a sensitivity test, and find that qualitative results remained consistent (Figures S12–S15 in Supporting Information S1). Furthermore, we conduct this analysis using NO_2 estimates from Cooper et al. (2020) and find similar patterns of disparities across racial/ethnic groups, though the distributions of NO_2 are smaller (Figure S16 in Supporting Information S1). For example, the medians in NO_2 at low POC schools in suburban, town, and rural areas were between 0.8 and 2.0 ppbv, depending on the poverty level, while high POC urban schools were only 3.2–4.0 ppbv. Despite the smaller differences using the Cooper et al. (2020) data set, the disparities across racial and ethnic groups are still statistically significant (Figure S17 in Supporting Information S1).

Relative to NO_2, there is less difference in $PM_{2.5}$ concentrations across poverty levels and between schools in urban and suburban, town, and rural areas (Figure 2b). This is unsurprising since the chemical lifetime of NO_2 is much shorter than for $PM_{2.5}$, which allows $PM_{2.5}$ to be more regionally uniform (additionally, the resolution of the satellite products used to develop the $PM_{2.5}$ product may not capture the scale of variability in surface $PM_{2.5}$). The distributions of $PM_{2.5}$ are similar across poverty levels. The 90th percentiles, however, are generally higher in the group with both greater fractions of students eligible for free or reduced lunch and high POC (Figure 2b). Relatively larger disparities are found across racial/ethnic groups for $PM_{2.5}$, since high POC schools have higher distributions of $PM_{2.5}$ than low POC schools within each poverty category and locale category with high statistical significance (Figure S11b in Supporting Information S1). Furthermore, similar to NO_2, the largest disparities are the result of low POC schools being concentrated in wealthier and more suburban, town, and rural areas, while high POC schools are concentrated in mostly urban and suburban areas and have higher levels of poverty (Figure 2c). Thus, the median annually averaged $PM_{2.5}$ concentration for low POC schools in moderately impoverished suburban, town, and rural areas is ∼1 μg m^{-3} lower than high POC, urban schools.

3.2. Regional Results

Although we show in Figure 2 that nationwide disparities exist, these disparities are, in part, due to regional differences in the location of different racial/ethnic and poverty groups. Thus, we also examine disparities in each state across the CONUS and find distinct patterns (Figure 3). To investigate how the disparities across race/ethnicity and poverty compare within states, we calculated the differences in mean NO_2 and $PM_{2.5}$ concentrations between (a) low POC and high POC schools in each state (Figures 3a and 3b) and (b) schools with the highest level of poverty and schools with the lowest level of poverty in each state (Figures 3c and 3d). For this analysis, we combine schools from urban, suburban, town, and rural locations. We define the "low POC" and "high POC" schools as those with less than 35% POC students and more than 61% POC students, based on the 40th and 60th percentiles for the percentage of POC students at schools nationwide. States in the Northeast and the Midwest show the largest disparities in NO_2 across racial/ethnic lines (Figures 3a and 3b). For example, there are large disparities in ambient NO_2 concentrations between high and low POC schools in New York (8.7 ppbv), Illinois (5.3 ppbv), and Michigan (4.5 ppbv). Figure 3c displays the differences in mean NO_2 between "high-poverty" and "low-poverty" schools in each state. These categories are defined as schools that have a percentage of students eligible for subsidized meals above 75% or below 25%, respectively. We find in Figure 3b that Northeastern and Midwestern states such as New York (7.8 ppbv), Illinois (4.1 ppbv), and Michigan (2.9 ppbv) have strong
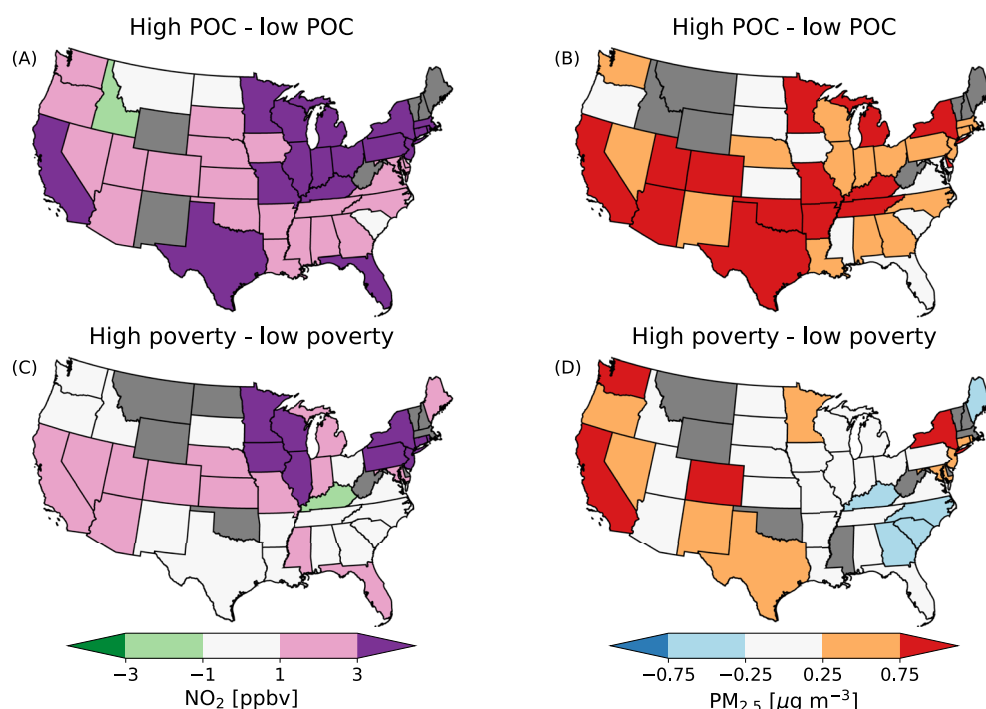
Figure 3. Difference in mean (a) NO$_2$ and (b) PM$_{2.5}$ between high people of color (POC) schools (>61% POC students based on the 60th percentile nationwide) and low POC schools (<35% POC students based on the 40th percentile nationwide). Difference in mean (c) NO$_2$ and (d) PM$_{2.5}$ between high-poverty (greater than 75% students eligible for free or reduced lunch) and low-poverty schools (fewer than 25% students eligible for free or reduced lunch). The colors are gray if there is no data for that state, there are fewer than 10 schools in either poverty or racial/ethnic categories, or if the difference was not found to be statistically significant using an independent *t*-test (Yuen, 1974).

disparities between high and low-poverty schools. Using the Cooper et al. (2020) data set, we find that fewer states have disparities of the same magnitude as in Figure 3, but the qualitative results are similar (Figure S18 in Supporting Information S1). For example, strong disparities were still found in New York and California across both racial/ethnic and poverty groups. On average, racial/ethnic disparities appear to be larger than just poverty disparities for most states, though these school category distinctions are not independent of each other. Much of the disparities in NO$_2$ appear to be associated with racial divides across urban, suburban, town, and rural areas. We investigate regional disparities in NO$_2$ in more detail in Section 3.2.

We find different patterns of disparities for PM$_{2.5}$ across race/ethnicity and poverty categories (Figures 3b and 3d), but most states still show increased PM$_{2.5}$ at schools with higher poverty levels and with more POC students. California has the largest difference in annually averaged PM$_{2.5}$ between high and low POC schools (2.4 µg m^{-3}) and between the poverty levels (2.1 µg m^{-3}). New York shows disparities between high and low POC schools (1.3 µg m^{-3}) but a smaller difference between poverty levels (1.0 µg m^{-3}). To note, the magnitudes of these disparities may be dependent based on the thresholds used to divide racial/ethnic categories and poverty levels, but the patterns of disparity remain consistent.

Concentrations of NO$_2$ are higher in cities, especially near sources such as major roadways and industrial areas (e.g., Anenberg et al., 2022). Thus, unsurprisingly, there are clear disparities in NO$_2$ concentrations at public schools across CONUS based on whether schools are in urban, suburban, town, or rural areas (Figure 2a). However, in certain regions, this urban/rural divide strongly intersects with poverty and race divisions (Figure 4 for Anenberg data; Figure S19 in Supporting Information S1 for Cooper data). For example, in New York (Figure 4a), wealthier, low POC public school students tend to be more dispersed across the state in suburban, town, and rural areas; while racial/ethnic minorities with higher levels of poverty are heavily concentrated in urban areas. This difference in locale leads to disparities of up to ∼11 ppbv NO$_2$ between high and low POC schools (with high statistical significance; Figure S20 in Supporting Information S1). Note that in Figure 4, we define "low POC" and "high POC" based on statewide percentiles of the proportion of POC students in each
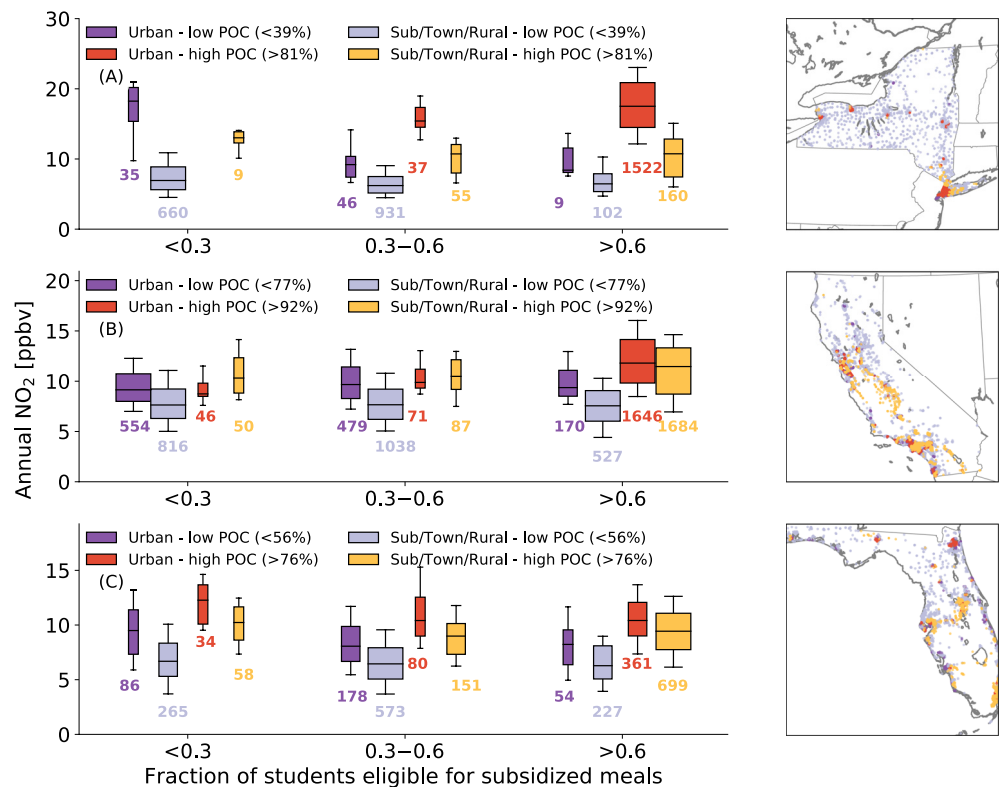
Figure 4. Boxplots of annually averaged NO_2 surface mixing ratios split into categories of poverty level in New York (a), California (b), and Florida (c). A greater fraction of free or reduced lunch indicates a higher level of poverty. Within each poverty-level bin, separate boxplots are shown for schools in urban and combined suburban, town, and rural locations for low people of color (POC) schools and high POC schools. The thresholds for high and low POC schools are based on the 60th and 40th percentile of the percentage of POC students in public schools within each state. The width of each boxplot is scaled for visual aid to three size categories corresponding to the number of schools in each distribution, which are listed near each distribution in corresponding colors.

school, instead of the nationwide percentiles used in Figures 2 and 3. In other regions, the locale category does not coincide with economic status.

In California, most schools are classified as urban or suburban, but NO_2 and $PM_{2.5}$ distributions still increase with poverty levels (Figures 3c and 3d), especially for urban high POC schools (Figure 4b). Additionally, concentrations are generally higher for high POC schools regardless of locale category. Thus, in California, we see some disparities across poverty levels that are not captured by differences in locale category (Figure 4b), though differences in medians were only statistically significant across poverty levels for high POC urban schools (Figure S21 in Supporting Information S1).

Finally, in some states, such as Florida (Figure 4c), there are disparities based on locale category and race/ethnicity, but not on school poverty-level. In Florida, there is a mix of schools with White and POC students in urban areas around the state, especially in Tampa and Jacksonville; and yet, there are still clear disparities between schools with high POC and low POC to high statistical significance (Figure S22 in Supporting Information S1).

Thus, we find that there are three major types of disparities that appear to exist in NO_2 concentrations at US public schools in different regions: (a) disparities between high POC/high-poverty and low POC/low-poverty schools based on locale category such that low-poverty schools with more White students are located in suburban, town, and rural areas with lower pollutant concentrations compared to high-poverty schools with more POC students concentrated in urban areas with higher pollutant concentrations; (b) within many suburban/urban areas, low-poverty schools with more White students have lower concentrations than corresponding high-poverty schools with more POC students; or (c) high POC schools have higher concentrations than low POC schools regardless of poverty level. We further investigated these second and third points, by repeating our analysis

only looking at schools within specific urban regions (Figures S23 and S24 in Supporting Information S1). For example, in the Bay Area of California, we found higher concentrations of NO_2 at high POC schools located in Chinatown, the Mission District, and Oakland, while low POC schools had lower NO_2 in the Richmond district, which is near the greenspace of Golden Gate Park, and other surrounding areas (Figure S24 in Supporting Information S1). We find similar qualitative results but smaller relative differences in $PM_{2.5}$ over New York, California, and Florida (Text S2 and Figure S25 in Supporting Information S1). The rural/urban divide is associated with the largest disparities in $PM_{2.5}$ concentrations over New York (Figure S25a in Supporting Information S1) and California (Figure S25b in Supporting Information S1). The analyses of each state separately show that disparities across racial/ethnic and poverty lines are complex, but generally ubiquitous in the US.

3.3. Limitations

There are several caveats to consider for our study. We are using ambient, annual average concentrations of pollutants at public schools. However, ambient concentrations of pollutants are different from personal exposure estimates, especially when children do not spend all of their time at schools and traditionally spend more time indoors than outdoors while at school. Hence, the results here represent nearby outdoor air as a proxy for exposure only during school times. Furthermore, as 80% of students live greater than 1.5 km from schools (McDonald, 2008), these concentrations may not be representative of their home exposure. Also, by using annually averaged pollutant concentrations, we are including summer months when students do not attend school, but a sensitivity analysis of $PM_{2.5}$ with summer months excluded resulted in the same qualitative conclusions (Figure S26 in Supporting Information S1).

Our analysis here focused on public schools and did not include private schools. It is unclear if including private schools would reinforce or change the patterns we have seen here. Furthermore, the fraction of students eligible for subsidized meals is an imperfect proxy for poverty and should not be confused with a direct measure for socioeconomic status, which requires knowledge of several financial and personal factors for each student.

Our quantitative results are also dependent on the data sets that we use in our analysis, and each data set has its own limitations and uncertainties. For example, the fine scale gradients of $PM_{2.5}$ used in this study may not be fully resolved because the model inputs were coarser than the output $PM_{2.5}$ resolution (van Donkelaar et al., 2021), which may cause us to underestimate disparities if schools are incorrectly grouped. This spatial resolution likely has little impact on our annually averaged national and state comparisons, but may be of greater concern if this analysis was replicated for specific urban regions. However, recent studies have shown that, while intra-urban gradients in primary pollutants were associated with racial/ethnic disparities at hyper-local scales (<100 m) (e.g., Chambliss et al., 2021), $PM_{2.5}$ and NO_2 disparities were driven by regional-scale differences, which implies that our results would be robust even with higher resolution data. The $PM_{2.5}$ and NO_2 data sets used may have larger uncertainties in remote areas, which have less dense ground-based monitors used for calibration (Anenberg et al., 2022; van Donkelaar et al., 2021). For NO_2, however, the scale of disparities across the urban-rural divide in our analysis was often around 10 ppb, while the root mean squared errors for the NO_2 data set against rural monitors was 2.26 ppb (Anenberg et al., 2022). Thus, even though concentrations at rural schools are less certain in our analysis than at urban schools, we remain confident in the qualitative results of our analysis. Finally, choosing a different data set altogether changes the quantitative results in our study. For example, our sensitivity analysis using the Cooper et al. (2020) data set shows lower concentrations of NO_2 on average (compared to Anenberg et al. (2022)) across most of the US. However, the qualitative results are similar, giving credence to the conclusions that we draw.

4. Conclusions

Our results contribute to a larger body of work documenting air pollution disparities that persist across local to federal scales in the US (Colmer et al., 2020; Gray et al., 2013; Hajat et al., 2015; Liu et al., 2021; Mohai, Lantz, et al., 2009; Tessum et al., 2019). We find that in most regions of the US, students who attend schools with higher percentages of racial-ethnic minority students and higher levels of poverty (as indicated by fraction of students eligible for free or reduced lunch) are associated with higher concentrations of both $PM_{2.5}$ and NO_2 compared to schools with lower percentages of racial-ethnic minority students and lower levels of poverty. Our results are consistent with past analyses that show disproportionate burdens of air pollution impacting Hispanic and Black or

African American children (Grineski & Collins, 2018; Morello-Frosch et al., 2002). This is not surprising as Black families in the US generally experience the highest levels of residential segregation (Massey & Denton, 1993) and tend to live in areas with increased health hazards in general (e.g., higher poverty levels, institutional disenfranchisement) (Bécares et al., 2012). We also add to a growing body of evidence that Asian or Asian/Pacific Islander children are disproportionately impacted by environmental hazards (e.g., Clark et al., 2014; Cushing et al., 2015; Grineski & Collins, 2018; Grineski et al., 2017; Liévanos, 2015; McKelvey et al., 2007; Morello-Frosch & Jesdale, 2006). Much of these disparities, but not all, appear to be connected to the rural-urban divide. However, we also find that even within urban environments, disparities exist across racial, ethnic, and poverty groups.

Disparities in air pollutants at schools will likely only exacerbate already existing disparities in the US because more impoverished and POC students will also suffer disproportionate, lifelong impacts from air pollution exposure on school and future job performance, as well as mental and physical health. Thus, it is crucial that air pollution is decreased around schools, with special attention being paid to those in high POC communities. Continuing to improve emission standards in automobiles and industrial sources will be key to improving air quality at schools for everyone, but especially high POC schools since they are often more likely to exist near major pollution sites such as heavily trafficked roads (e.g., Chakraborty & Zandbergen, 2007; Green et al., 2004; Maantay, 2002).

Finally, future investigations of disparities in air pollution at US schools should develop new knowledge on: (a) estimates of indoor air pollution and personal exposure estimates for students, (b) how building design and socioeconomic factors impact the infiltration of outdoor air into schools, (c) estimates of air pollutant concentrations and exposure during school commutes, (d) emissions sources and other pollutants (besides NO_2 and $PM_{2.5}$) that may impact air quality at schools, and (e) how social, environmental, geographical, and financial factors lead to disparities in schools. In addition to working to reduce air pollution in general, this knowledge should be used to develop specific policies that can be effective in reducing disparities.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The NO_2 data set described by Anenberg et al. (2022) is available at Mohegh and Anenberg (2021) (https://figshare.com/articles/dataset/Global_surface_NO2_concentrations_1990-2020/12968114). The NO_2 data set described by Cooper et al. (2020) is made available at WUSTL (2022a) (an updated version can be found at: https://sites.wustl.edu/acag/datasets/surface-no2/). The $PM_{2.5}$ data set described by van Donkelaar et al. (2021) is available at WUSTL (2022b) (https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.02). The US public school data set is available at the National Center for Education Statistics Elementary/Secondary Information System table generator (https://nces.ed.gov/ccd/elsi/tableGenerator.aspx).

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