



Patterns of distributive environmental inequity under different PM_{2.5} air pollution scenarios for Salt Lake County public schools

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ABSTRACT

Previous studies have cataloged social disparities in air pollution exposure in US public schools with respect to race/ethnicity and socioeconomic status. These studies rely upon chronic, averaged measures of air pollution, which fosters a static conception of exposure disparities. This paper examines PM_{2.5} exposure disparities in Salt Lake County (SLC), Utah public schools under three different PM_{2.5} scenarios—relatively clean air, a moderate winter persistent cold air pool (PCAP), and a major winter PCAP—with respect to race/ethnicity, economic deprivation, student age, and school type. We pair demographic data for SLC schools ($n = 174$) with modelled PM_{2.5} values, obtained from a distributed network of sensors placed through a community-university partnership. Results from generalized estimating equations controlling for school district clustering and other covariates reveal that patterns of social inequality vary under different PM_{2.5} pollution scenarios. Charter schools and schools serving economically deprived students experienced disproportionate exposure during relatively clean air and moderate PM_{2.5} PCAP conditions, but those inequalities attenuated under major PCAP conditions. Schools with higher proportions of racial/ethnic minority students were unequally exposed under all PM_{2.5} pollution scenarios, reflecting the robustness of racial/ethnic disparities in exposure. The findings speak to the need for policy changes to protect school-aged children from environmental harm in SLC and elsewhere.

Credit statement

Casey Mullen: Writing - original draft; Formal analysis, Sara Grineski: writing-review & editing; Supervision; Conceptualization; Project administration, Timothy Collins: writing-review & editing; Conceptualization; Supervision; Wei Xing: Methodology; Software; Formal analysis, Ross Whitaker: mentorship for methodology and Software; Funding acquisition, Tofigh Sayahi: Investigation; Validation, Tom Becnel: sensor network development; data interpretation, Pascal Goffin: Data curation, Pierre-Emmanuel Gaillardon: mentorship for sensor network development; data interpretation; Funding acquisition, Miriah Meyer: Funding acquisition, Kerry Kelly: Conceptualization, writing & editing; data interpretation; Validation; Funding acquisition.

1. Introduction

Air pollution is an important hazard to human health, and fine particulate matter (PM_{2.5}) pollution is a key driver of air-pollution's adverse health effects (World Health Organization, 2019; Anderson et al., 2012; Brook et al., 2010). PM_{2.5} particles are fine, inhalable particles that are 2.5 μm in diameter or less; thus, PM_{2.5} exposure poses a serious hazard to the cardiopulmonary system of the human body (Anderson et al., 2012; Brook et al., 2010). Although the majority of air-pollution health studies have focused on long-term pollution exposure, more recent studies have reported adverse health outcomes, including mortality (Lin et al., 2017a; Lin et al., 2017b) and decreased lung function in children with severe asthma (Yamazaki et al., 2011), associated with increased PM_{2.5} levels in the previous few hours.

Children are more susceptible to the effects of PM_{2.5} due to their

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small body stature and growing lungs (Brockmeyer & D'Anguilli, 2016; Landrigan et al., 2010). Children are also more often rooted in specific local environments than are adults, and they spend substantial time at school (Kweon et al., 2018). Increased exposure to air pollution at school is associated with negative health effects for students (Kweon et al., 2018; McConnell et al., 2006; Wang et al., 2009; Buthumrung et al., 2008; Volk et al., 2011) as well as poorer academic performance and attendance (Grineski et al., 2020; Kweon et al., 2018; Pastor et al., 2006; Mohai et al., 2011). This study focuses on characterizing social inequalities in PM_{2.5} exposures at school under different weather scenarios in Salt Lake County (SLC), Utah public schools.

The effects of school-based exposure on children are troubling, and not all children are equally exposed to air pollution at school. Differences in the distribution of burdens, such as concentrations of air pollutants, are considered disparities and the measurement of disparities is an important feature of distributional environmental justice research (Schlosberg, 2009; Bell and Carrick, 2017). Several distributional environmental injustice studies have found that racial and ethnic minority children are overrepresented in schools with higher pollution levels (Kweon et al., 2018; Pastor et al., 2006; Chakraborty and Zandbergen, 2007; Grineski and Collins, 2018; Collins et al., 2019; Morello-Frosch et al., 2002) including, higher levels of PM_{2.5} emissions from road traffic (Gaffron and Niemeier, 2015). Schools serving economically deprived students are also exposed to higher levels of pollution on average in the US (Grineski and Collins, 2018; Collins et al., 2019) and in several US states, such as California (Pastor et al., 2006) and North Carolina (Salvezen and Zambito, 2010). Although age is less often investigated, schools serving younger students have greater exposures than those serving older students (Grineski and Collins, 2018; Collins et al., 2019). While notable, these distributive environmental injustice studies specific to schools and schoolchildren have examined a limited set of social inequality indicators, limiting knowledge about social disparities and exposure.

An important limitation of the distributive environmental injustice literature on schools, as well as the extant environmental injustice literature in general, has been the long-standing reliance upon chronic, averaged measures of air pollution (e.g., Anderson et al., 2018; Mazaheri et al., 2013). This reliance has fostered a static conception of exposure disparities and provided a limited basis for interventions designed to reduce schoolchildren's exposures to temporally variable levels of air pollution. Nearly 20 years ago, Pellow (2000) observed that while environmental injustices are inherently temporally dynamic, analysts have typically conceived of distributive environmental injustice as a static phenomenon. This critique remains relevant today and is reflected in the still-common use of single, static measures of air pollution exposures in many environmental injustice studies. For example, several school-based studies have relied on measures of air pollution from the US Environmental Protection Agency's (EPA) National Air Toxics Assessment (NATA) (Kweon et al., 2018; Pastor et al., 2002, 2006; Grineski and Collins, 2018; Morello-Frosch et al., 2002). While a strength of the NATA data are the complex spatial modelling and weighting by health risks, they do not capture temporal variability, being that they are annually averaged and cover only four of the past 20 years (1999, 2005, 2011, 2014). Other school-based studies have used locally generated surfaces based on state air monitoring networks (e.g., Gaffron and Niemeier [2015]). While these data can be used to create temporally granular measures of exposure, environmental justice analysts have typically been averaged to create one measure of chronic pollution (e.g., annual PM_{2.5}) and are limited by sparseness of the monitoring network that propagates unacceptable spatial error (Steinle et al., 2013; Bell et al., 2011).

This conception of pollution as a static phenomenon is flawed when considering the temporal dynamism of air pollution, especially in a place like SLC, Utah, which has dramatic seasonal variability and complex topography that periodically traps pollution in a valley surrounded by high mountains (Holzworth, 1967; Whiteman et al., 2014).

During the winter, cold air settles in SLC (and many mountain valleys) and high-pressure systems move in, acting like a lid, trapping pollution. These episodes are known as persistent cold air pools (PCAPs), and colloquially as inversions. The spatial distribution of peak PM_{2.5} concentrations tends to be controlled by elevation, with lower elevation locations nearest pollution emissions sources on the valley floor having the highest concentrations for the longest durations (Silcox et al., 2012). The main sources of primary PM_{2.5} in SLC during the winter are, in rank order, mobile sources such as vehicles, trains, and aircraft; smaller stationary sources, like home heating, smoke from wood burning, and emissions from small shops and restaurants; and large industrial and commercial facilities (Call, 2018). Secondary PM comprises more than one half of overall PM_{2.5} levels in the study area during PCAPs when gases such as sulfur dioxide, NO_x, and VOCs react with other gasses in the atmosphere, such as ammonia, to form tiny particles. PCAPs provide ideal conditions for secondary PM_{2.5} to form (Utah Division of Air Quality, 2019; Kelly et al., 2013). In any given winter, SLC experiences PCAPs which can last for a few days or more than two weeks. This means that a measure of annual average PM_{2.5} fails to capture SLC's different PM_{2.5} scenarios that are the focus of local public health concerns. Studies that account for high spatiotemporal variability are needed to advance understanding of social disparities of air pollution exposures within this context (Collins and Grineski, 2019).

This study extends from prior EJ studies focused on SLC and schoolchildren. First, we account for the high level of spatial and temporal variability in PM_{2.5} by demonstrating how social disparities in exposures to PM_{2.5} varied under three different PM_{2.5} scenarios associated with low wind conditions. We leveraged data from a community-university partnership through the University of Utah's Air Quality and U (AQ&U) network, from which we constructed high-resolution (spatially and temporally) PM_{2.5} estimates (Sayahi et al., 2019a; Sayahi et al., 2019b; Becnel et al., 2019). Second, we examined school-level variables that have not received focus in prior school-based environmental injustice research, i.e., Title I status, charter school type, and alternative or special education school types. Third, with a focus on PM_{2.5}, we sought to add to the small literature on social disparities in school-level exposure to one of the most health-harming forms of air pollution.

This study addresses the following research question: is PM_{2.5} exposure distributed unjustly based on race/ethnicity, economic deprivation, student age and school type in three different scenarios, including a relatively clean fall day, a moderate winter PCAP, and a major winter PCAP?

2. Material and methods

2.1. Study area: Salt Lake County

SLC is the most populated county in Utah with over 1 million residents. The county has serious air quality problems; it periodically experiences the highest PM_{2.5} (particulate matter less than 2.5 µm in diameter) pollution in the US (Shenefelt, 2016). Numerous adverse human health effects have been associated with this exposure in SLC (Beard et al., 2012; Hammoud et al., 2010; Pope Iber, 2000; Pope III et al., 1999; Pope III et al., 2017; Utah Division of Air Quality, 2018). SLC residents live in a serious non-attainment area for 24-h PM_{2.5} pollution (Utah Division of Air Quality, 2018). PM_{2.5} is primarily a concern during winter, and typically SLC exceeds the National Ambient Air Quality Standard (NAAQS) on 18 days per year (Whiteman et al., 2014).

Socially, SLC has a diverse populace, which runs counter to general perception in the US that the area's population is highly homogeneous—i.e., overwhelmingly composed of non-Hispanic White members of the Church of Jesus Christ of Latter Day Saints (formerly known as Mormons). Data from the American Community Survey for 2015 indicate that although the population is predominantly (73%)

non-Hispanic/Latino White, it also includes more than 300,000 (27%) racial/ethnic minority residents. The only distributive environmental injustice study conducted in SLC revealed strong patterns of injustice with respect to race/ethnicity across a suite of chronic, averaged air pollution measures (Collins and Grineski, 2019).

2.2. Unit of analysis: Salt Lake County public schools

We downloaded the geographic locations and demographics of all 312 public schools in SLC from the National Center for Education Statistics (NCES) using the ELSi Table Generator tool. We selected 2016–2017 data because it was the most recent school year data available and it aligns best with our PM_{2.5} data. This ELSi tool provides users with access to the Common Core of Data (CCD), which is the US Department of Education's primary database on public elementary and secondary schools in the United States. These data have been used in prior studies of school-based environmental injustice (Grineski and Collins, 2018; Collins et al., 2019). The CCD surveys are conducted annually at all public elementary and secondary schools throughout the US. CCD contains general descriptive information on schools and on their students and staff. Of relevance to this project, we downloaded the latitude and longitude of each school, information about the racial/ethnic make-up of the student body, total enrollment, lowest and highest grades offered at the school, and school type characteristics. We first removed schools that fell outside of our PM_{2.5} extent ($n = 132$), which is discussed below, and then removed additional schools from within our extent that had fewer than 50 students enrolled in the 2016–2017 school year ($n = 6$) to create more stable proportion variables, leaving 174 schools in our analysis. Fig. 1 shows the schools included in the study, which are located across 11 municipalities and 5 school districts.

2.3. Dependent variables

We utilized three dependent variables, each associated with a different air pollution scenario: clean air, moderate PCAP, and major PCAP. Each dependent variable represents the mean 10-min concentration of PM_{2.5} over a 48-h period at each school. We also examined variables for the median 10-min concentration for each of the three scenarios, which we report in a sensitivity analysis. We selected 10-min increments to capture the temporal and spatial variability that can occur due to meteorology and emissions patterns over the complex terrain of SLC. Indeed, an examination of the two DAQ sensor readings during each two day scenario reveals substantial variability in the hourly PM_{2.5} concentrations. Concentrations varied by more than a factor of 7 for the clean air scenario and more than a factor of 3 for the moderate and major PCAPs (see Table 1). This substantial variability between the hourly measurements suggests that a finer temporal resolution is warranted. Although using the 48-h mean PM_{2.5} concentration developed from the 10-min averages would be the same as using the hourly averages, we consider the effect of using the median 10-min PM_{2.5} concentrations in our sensitivity analysis.

The three sets of PM_{2.5} concentration measurements are generated from the AQ&U infrastructure during three 48-h time periods (Becnel et al., 2019). AQ&U contains more than 100 nodes, and it includes measurements from the Utah Division of Air Quality's federal equivalent methods (FEMs, 2 Sharp model 5030i monitors, ThermoFisher, Franklin, MA), and the University of Utah's Air U and PurpleAir low-cost sensor nodes. Community members and schools participate in the network by hosting air-quality sensor nodes (Becnel et al., 2019). Fig. 1 shows the locations of the four different types of sensors in the study area.

The Plantower PMS sensor provides the PM_{2.5} measurements in the University of Utah's AirU nodes (PMS 3003) and the PurpleAir (PA I, PMS 1003 or PA II, PMS 5003) nodes. The three models of PMS sensors used in these nodes have similar configurations, operate at the same

laser wavelength, and employ the same operating principles. These sensors and the methods used to calibrate them are described elsewhere (Sayahi et al., 2019a; Sayahi et al., 2019b; Kelly et al., 2017). Briefly, the PMS sensors measure 90-degree light scattering with a photo-detector that converts scattered laser light into PM_{2.5} concentration. All of the AirU and selected PurpleAir PM_{2.5} sensors were calibrated in the laboratory prior to deployment and in the field by collocating the sensor nodes with the Utah Division of Air Quality's FEMs and developing calibration factors for each model of PMS sensor and for each season (Sayahi et al., 2019a; Sayahi et al., 2019b; Kelly et al., 2017). See Table S-1 in the supplemental material for the seasonal corrections for each sensor type.

The PMS sensors collect measurements every second, and AQ&U average these measurements over 60 s and transmits the measurements over the host's Wi-Fi to an Influx database (AirU) or a ThingSpeak database (PurpleAir). The public can access sensor data through the AQ&U website (see <https://aqandu.org/>) or can download raw sensor data through an API (see <http://air.eng.utah.edu/dbapi/api/dashboard>). As previously stated, we aggregated the 60-s readings to 10-min intervals.

We selected three two-day periods to represent clean air, moderate PCAP, and severe PCAP scenarios. Table 2 shows the numbers of different types of sensors operating during each scenario and the percentage of the study period that each type of sensor was providing data. We used consecutive two-day periods because these were the longest time periods in which we could capture consistent meteorological conditions (at the two state air-quality monitoring stations) for the major PCAP. Table 2 summarizes the PM_{2.5} concentrations and meteorological conditions, including valley heat deficit (VHD), during these scenarios. Using two full days also allows us to capture any diurnal wind patterns in this region (Williams, 1969; Stewart et al., 2002). Wind roses for each scenario are included in the supplementary material (see Figs. S1–S3). During all three scenarios, the winds were light with 95%, 95%, and 84% of hourly average winds at or below 4.5 mph for the major, minor, and clean air days, respectively. Because PCAPs are associated with low wind patterns, all three two-day periods in the study share similar low wind patterns, which gives meteorological consistency in our analyses. Wind speed and direction play a significant role in air pollutant transport when wind speeds exceed 4.5 mph in urban areas such as SLC (Kim et al., 2015). VHD was the primary indicator of a PCAP, and it was calculated from air density and potential temperature, collected from twice-daily rawinsonde soundings collected at the Salt Lake City International Airport (Whiteman et al., 2014). Generally, VHDs greater than 4 are indicative of a PCAP, with greater VHDs indicating more severe PCAPs. Consequently, the major PCAP had the highest average VHD and the highest PM_{2.5} concentrations. The consistently low temperatures, low wind speeds, and elevated relative humidity (RH) are also indicative of a strong PCAP (Whiteman et al., 2014). The clean scenario is typical of the well-mixed atmosphere and the low PM_{2.5} concentrations of SLC in the fall.

We needed to generate a spatiotemporal map of PM measurements from the sensors in order to generate PM values for each school. We use the classical Gaussian process (GP) model for spatiotemporal regression, which follows a Bayesian formulation. The data from the sensors are considered as a set of noisy measurements. The GP model assumes that the actual spatiotemporal patterns of PM_{2.5} are from a class of functions with defined correlations among points that are separated by space ($\mathbf{x}$), altitude ($\mathbf{a}$) and time ($\mathbf{t}$). Thus, the sensor measurements are generated from a process, $y = f(\mathbf{x}, \mathbf{a}, \mathbf{t}) + \epsilon$, where ϵ is assumed to be independent, zero-mean Gaussian noise, so that $\epsilon \sim G(0, \sigma_\epsilon)$, and σ_ϵ is estimated from the calibration of the sensors (see Table S-1, Supplementary Material). The function f is itself from a multivariate Gaussian (normal) distribution, $f \sim G(\mu_f, \Sigma_f)$. The mean signal, μ_f , is the average of all measurements over all space and time. The covariance of, Σ_f , is defined by a set of correlation functions, $c(\cdot, \cdot)$, that describe how correlations between disparate values decrease with increasing distance in space, time, and altitude. For this work, we use correlation functions

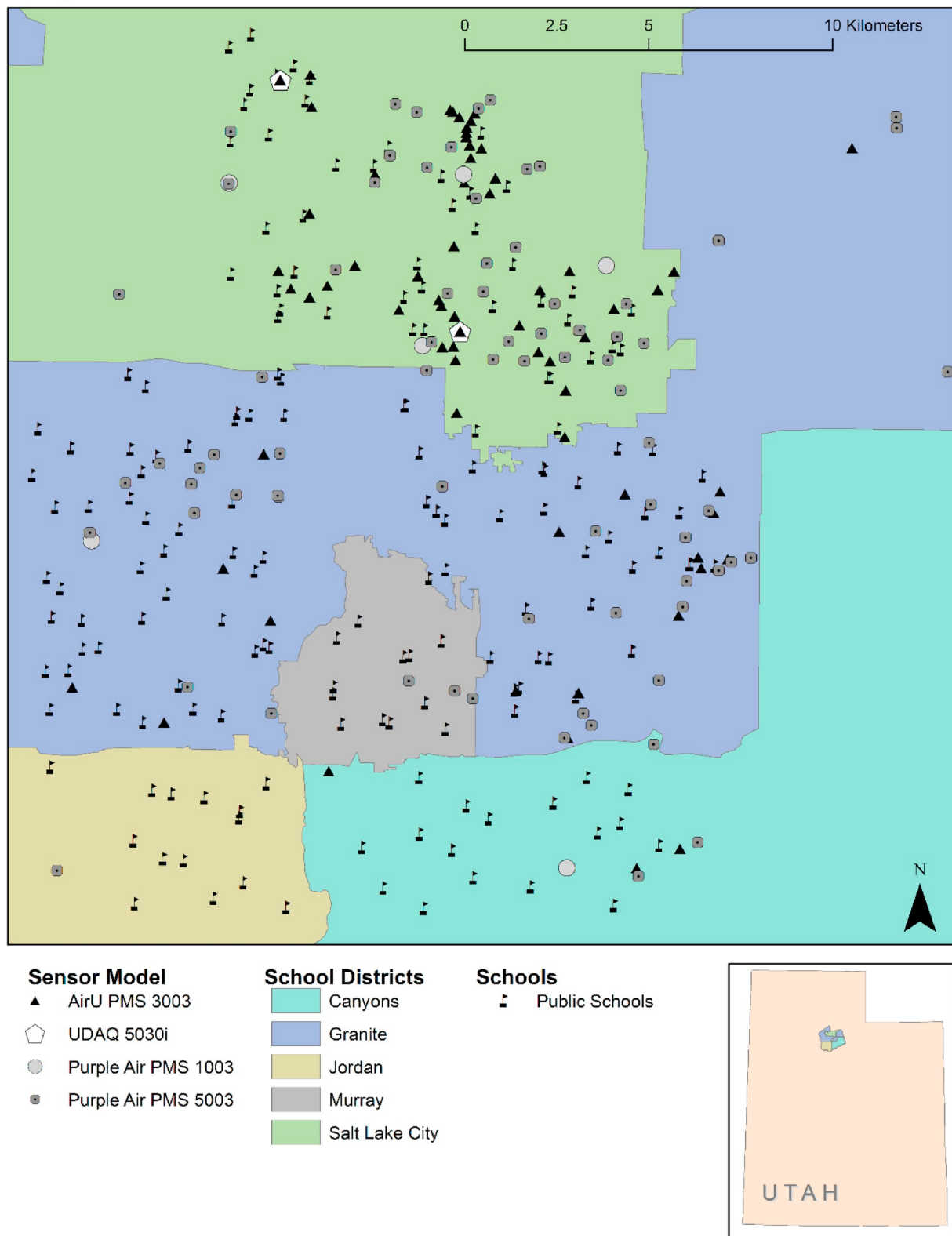


Fig. 1. Study area map showing locations of public schools included in the study ($n = 174$) and the $PM_{2.5}$ sensors.

that are separable,

$$c((x, a, t), x', a', t') = \theta_0 c_x(x, x') c_a(a, a') (c_t(t, t') + \theta_1 \delta(t, t')) \quad (1)$$

$$+ \theta_2 \delta((x, a, t), (x', a', t')) \quad (2)$$

where two locations in space and time are denoted with and without a

prime. The $\delta(\cdot)$ term is the.

Dirac delta. The $\theta_1 \delta(\cdot)$ term for the time parameter adds an additional noise term and reflects the particular structure of that signal, which is generally not observed to be smooth (even accounting for sensor noise). The individual correlation functions are:

Table 1

Date range for each scenario, number of sensor nodes in the AQ&U infrastructure during the date range, PM_{2.5} concentrations and meteorological parameters from Utah's Department of Air Quality's Hawthorne monitoring station.

	Clean Air	Moderate PCAP	Major PCAP
Dates	10/23–10/24/18	1/4–1/5/2019	12/12–12/13/17
# of sensors	193*	221	56*
Mean valley heat deficit (12-hr range) in MJ/m ²	1.62 (0.456–2.38)	8.36 (2.8–12.8)	13.2 (12.5–14.5)
Mean PM _{2.5} (1-hr PM _{2.5} range) in µg/m ³	3.9 (1.1–8.1)	36.7 (17.8–63.5)	54 (27–80)
Mean relative humidity (range) in %	53.8 (30.7–79.4)	65 (46.4–71.6)	75 (65.9–80.3)
Mean Temperature (range) in °C	14 (7.5–21)	−3.4 (−8.9–4)	−1.4 (−3.9–5.0)
Mean wind speed (range) in mph	3.0 (0.6–8.1)	2.1 (0.6–5.2)	2.7 (1.4–5.5)

Note: *one sensor was removed from 10/23–10/24/18 and one from the 12/12–12/13/17 period for reading greater than 350 µg/m³ for at least 1 h and for exhibiting a temporal pattern unlike those of its nearest neighbors.

Table 2

Summary statistics by scenario for the different model sensors.

	Clean Air		Moderate PCAP		Major PCAP	
Sensor Model	N operating	% data	N operating	% data	N operating	% data
UDAQ	2	100	2	100	1	100
AirU 3003	64	98.2	66	87.6	2	96.9
Purple Air 1003	8	100.0	0	0.0	0	0.0
Purple Air 5003	119	98.7	125	96.7	39	99.8
Total	193		193		42	

Note: UDAQ=Utah Division of Air Quality; % data: percent of time that all sensors of this model were providing measurements.

$$c_{\alpha}(\alpha, \alpha') = \exp(\|\alpha - \alpha'\|^2 / (2\sigma_{\alpha}^2)) \text{ where } \alpha \in \{x, a, t\}. \quad (3)$$

The GP formulation provides for an estimate of the posterior of $f(\cdot)$, which is conditioned on the noisy measurements, in the form of a normal distribution over the space of functions from which $f(\cdot)$ is drawn. In this way, we can compute, in a closed, linear-algebraic form, the mean of this distribution and its covariance. In communicating the model, we typically show the mean of the posterior, which we call the *air-quality estimate* and the variance or the standard deviation at each point in the domain, which we call the *error* or *uncertainty*.

The parameters consist of the scales in the correlations, the σ 's, for each of the quantities (space, altitude, time), and the θ terms that control the variation in the signals relative to the sensor noise and the correlations between nearby estimates (i.e. smoothness). These parameters are estimated from the input data using maximum likelihood estimation (MLE). We have observed that different air-quality events have different signal characteristics. Thus, for each scenario the model hyperparameters are estimated using MLE and the predictive posteriors are then calculated.

Figs. S-4–S-6 (in supplemental material) compare the Gaussian process (GP) PM_{2.5} predictions (excluding the UDAQ measurements) at the locations of the UDAQ stations during each scenario, demonstrating that the model predictions generally agree with PM_{2.5} trends exhibited by the reference monitors. The root-mean-square error (RMSE) for each of these predictions ranged from 74% to 94% (clean air scenario) to 12–19% (moderate and major PCAPs) (see Table S-2 in Supplemental Material). The RMSEs are lowest (on a percent basis) for the moderate and major PCAP, likely because PM_{2.5} concentrations were well above the sensor's limit of detection (5 µg/m³, Sayahi et al. 2019a,b). The RMSEs for the GP model predictions are on the lower edge of the range of those reported. For example, Zikova et al. (2017) reported a RMSE of 475% for calibration of sixty-six Speck sensors from two outdoor campaigns (7 days with an average PM_{2.5} concentration of 1.45 µg/m³). Zheng et al. (2018) reported RMSEs that ranged from 18 to 32% (hourly measurements) for linear calibrations of co-located PMS3003 sensors and reference measurements in Durham, North Carolina and Kanpur, India.

2.4. Independent variables

We examined five groups of independent variables. (1) For *racial/ethnic composition*, we created variables for two minority racial/ethnic groups: the percentage of students identified as Hispanic (of any race), and the percentage of students identified as non-Hispanic and from a racial/ethnic minority background (including black, multi-racial, Native-American, Asian, and Pacific Islander/Hawaiian students). These non-Hispanic minority groups were combined due to small counts in many of the study area schools. In the multivariate models, these two variables can be interpreted in reference to the percentage of non-Hispanic white students, which serves as the reference group.

We employed one variable to gauge (2) *economic deprivation*. We used the school's status as a Title I eligible institution as Title I schools serve a high percentage of economically disadvantaged students and receive financial assistance from the federal government in order to help students meet academic standards. This variable has been used in other studies to measure the socioeconomic status of schools (Grineski et al., 2018). The percentage of students qualifying for free and reduced-price meals (FRPM) is a more commonly used measure of economic deprivation (Pastor et al., 2006; Grineski and Collins, 2018; Nicholson et al., 2014). It has been used in environmental justice studies of schools (Mohai et al., 2011; Grineski and Collins, 2018; Morello-Frosch et al., 2002; Salvezen & Zambito, 2010) and it is available through ELSi. While we created this variable, we could not use it in our multivariate model due to collinearity with the percent Hispanic variable. The two variables were correlated at 0.77.

We created a dichotomous variable for primary versus secondary schools to capture (3) *student age*, based on the grade level of students that each school served using the variables “highest” and “lowest grade offered at the school”. Primary schools are those with the highest grade offered being pre-kindergarten, kindergarten, or first through sixth grades. Schools with the highest grade offered being seventh through twelfth were coded as secondary schools, as were schools serving all grades.

We used two variables to examine the (4) *school type*. First, we included a variable that gauged whether the public school is a charter school or not. Charter schools are publicly funded under a legislative contract with a governing body, such as the state or district; they are exempt from some state or local rules and regulations that apply to traditional public schools (NCES, 2019). Second, we included a variable for the status of a school as an alternative or special education school with the reference category being regular public schools. Alternative schools serve students who are at risk of academic failure, and special education schools serve students with learning and developmental disabilities as well as behavioral issues (NCES, 2010). Alternative and special education schools were combined into one variable due to small counts.

To control for urban context, we use a (5) *population density* variable (i.e., total population divided by area). This represents the population density in the census tract containing each public school. This is

important to control for, since greater population density is usually associated with greater air pollution-producing activities (Chakraborty et al., 2014).

2.5. Analysis approach

We employed generalized estimating equations (GEEs) to test for distributional injustices and to examine how patterns of injustice varied under the three different PM_{2.5} exposure scenarios. GEEs enable us to examine environmental inequalities in reference to non-normally distributed dependent variables while accounting for geographic clustering (Liang and Zeger, 1986; Collins et al., 2015). We report results from GEEs for three separate PM_{2.5} exposure scenarios: clean air conditions, moderate PCAP conditions, and major PCAP conditions. In the sensitivity analysis, we replicated these analyses using median PM_{2.5} instead of mean.

GEEs require the specification of an intracluster dependency correlation matrix, otherwise known as a working correlation matrix (Liang and Zeger, 1986; Grineski et al., 2018). The correlation structure specified for this study was *exchangeable*, which is a specification that assumes constant intra-cluster dependency so that all of the off-diagonal elements of the correlation matrix are equal. It has been used in similar studies (Grineski and Collins, 2018; Collins et al., 2015).

To fit a GEE model, clusters of observations must be defined based on the assumption that observations from within a cluster are correlated, while observations from different clusters are independent (Garson, 2012). For this study, we used school districts to define clusters. School districts operate relatively independent of each other and are decision-makers with respect to school-level environmental policies (Grineski and Collins, 2019). District-level school boards can advocate for the environmental health of children. They make decisions relevant to environmental health, including selecting sites and designs for major school building projects, purchasing school busses, and implementing indoor air quality initiatives (Sampson, 2012).

To select the best fitting model, we estimated a series of GEEs by varying the model specifications. We tested normal, gamma and inverse Gaussian distributions with logarithmic (log) and identity link functions. We considered gamma and inverse Gaussian, in addition to normal, because there were no values less than zero among our dependent variables and these seemed like reasonable options given the histograms of our dependent variables. To compare fit between the six models (three distributions and two link functions) for each scenario, we reviewed the quasi-likelihood under independence model criterion (QIC) values. We selected the model with the lowest reported QIC value, as that indicated the best fit (Garson, 2012). Therefore, we present results using the inverse Gaussian distribution with a log link function, since it was the best fitting specification. The log link function represents natural logarithmic relationships between variables, as opposed to the identity link function, which models relationships between dependent and independent variables linearly.

We tested for multicollinearity using the multicollinearity condition index (MCI), which we calculated for the combination of explanatory variables included in the GEEs. The MCI was smaller than 6.0, indicating the absence of serious collinearity problems. The statistical significance of the independent variables was estimated on the basis of the Wald's chi-squared test. Continuous independent variables were standardized before inclusion in these models in order to make coefficients directly comparable. For the purposes of this study, we define statistical significance as $p < 0.05$.

3. Results

Table 3 presents descriptive statistics for all of the analysis variables. In regards to the dependent variables, shifting patterns of PM_{2.5} under the three scenarios are evident. For the clean day, the average PM_{2.5} concentration was 4.25 $\mu\text{g}/\text{m}^3$, for the moderate PCAP it was

Table 3
Descriptive Statistics of Analysis Variables (n = 174 schools).

Continuous Variables	N	Min.	Max.	Mean	Std. Dev
PM _{2.5} : Clean Air (mean)	174	1.52	6.05	4.25	0.891
PM _{2.5} : Moderate PCAP (mean)	174	19.7	36.8	32.0	3.34
PM _{2.5} : Major PCAP (mean)	174	30.4	57.5	45.0	5.49
% Hispanic Students	174	0	93.7	31.1	21.4
% Non-Hispanic Minority Students	174	0	69.3	15.1	8.936
Population Density (pers/km ²)	174	14.2	50,405	1945	940
Dichotomous Variables	N	Yes (N)	Yes (%)	No (N)	No (%)
Primary school	174	103	59.2	71	40.8
Charter School	174	28	16.1	146	83.4
Alternative/Special Ed School	174	9	5.2	165	94.8
Title I Eligible	174	79	45.4	95	54.6

32 $\mu\text{g}/\text{m}^3$, and for the major PCAP it was 45 $\mu\text{g}/\text{m}^3$. The averages bely the spatial variability in PM_{2.5} concentrations, which are depicted at each school in Fig. 2. When the air was cleanest, the areas of highest PM_{2.5} were in the north and central-west portions of the study area. During the moderate PCAP, the highest PM_{2.5} concentrations were in the central and west-central portions of the study area, along the Interstate Highway-15 corridor. During the major PCAP, the pattern was similar to the moderate PCAP with the exception of the southeast near the loop freeway; that region had low PM_{2.5} concentrations during the major PCAP and high PM_{2.5} concentrations during the moderate PCAP. In all three scenarios, the lowest PM_{2.5} concentrations were on the south and east side of the study area along the bench where elevation ascends from the valley floor.

Fig. 3 depicts the standard deviations of the PM_{2.5} levels at each school. For the clean air scenario, the lowest standard deviations are associated with higher elevations and more residential areas. The greater standard deviations are associated with more urban areas and areas with less ground cover (including the Salt Lake County Landfill) (Collins and Dronova, 2019). Urban areas are more likely to experience diurnal differences in traffic-related PM_{2.5} than higher elevation, residential areas, and the clean air scenario included wind-speeds ranging from 0.6 to 8 mph, which could result in larger variations in wind-generated PM_{2.5} in areas with less ground cover. The moderate and major PCAP scenarios show a similar pattern for standard deviation, with larger standard deviations associated with higher elevations and regions near the outflows of mountain canyons. PM_{2.5} concentrations during a PCAP event exhibit diurnal patterns, associated with clean, cold air flowing into SLC from mountain canyons and with variations in the mixing height that cause elevated areas to oscillate between being within the PCAP and being above it (Silcox et al., 2012).

Table 3 shows the demographics of each school. The average school had a student body that was 31% Hispanic, 15% non-Hispanic minority, and 54% white. For the economic deprivation indicator, of 174 public schools in SLC, 45.4% were Title I eligible (i.e., economically deprived). Just over half of the schools were primary schools and 16.1% were charter schools; 5.2% were alternative or special education schools. The average population density in our study area was 1945 persons per square kilometer.

Table 4 presents results from the three GEEs predicting PM_{2.5} at SLC Public Schools. In what follows, we present the results in order from the relatively clean day, to the moderate PCAP, to the major PCAP. The exponentiated coefficient values for the proportion variables in the multivariate models shown in Table 4 are interpretable as the percent change in the dependent variable (after the Exp (Coeff.) is subtracted from 1 and multiplied by 100) for each one standard deviation above the mean increase in each independent variable. That value can be converted into the change in PM_{2.5} concentration by subtracting the Exp (Coeff.) from 1 and then multiplying by the range (maximum minus minimum) in PM_{2.5} concentrations.

When predicting PM_{2.5} concentrations during the relatively clean

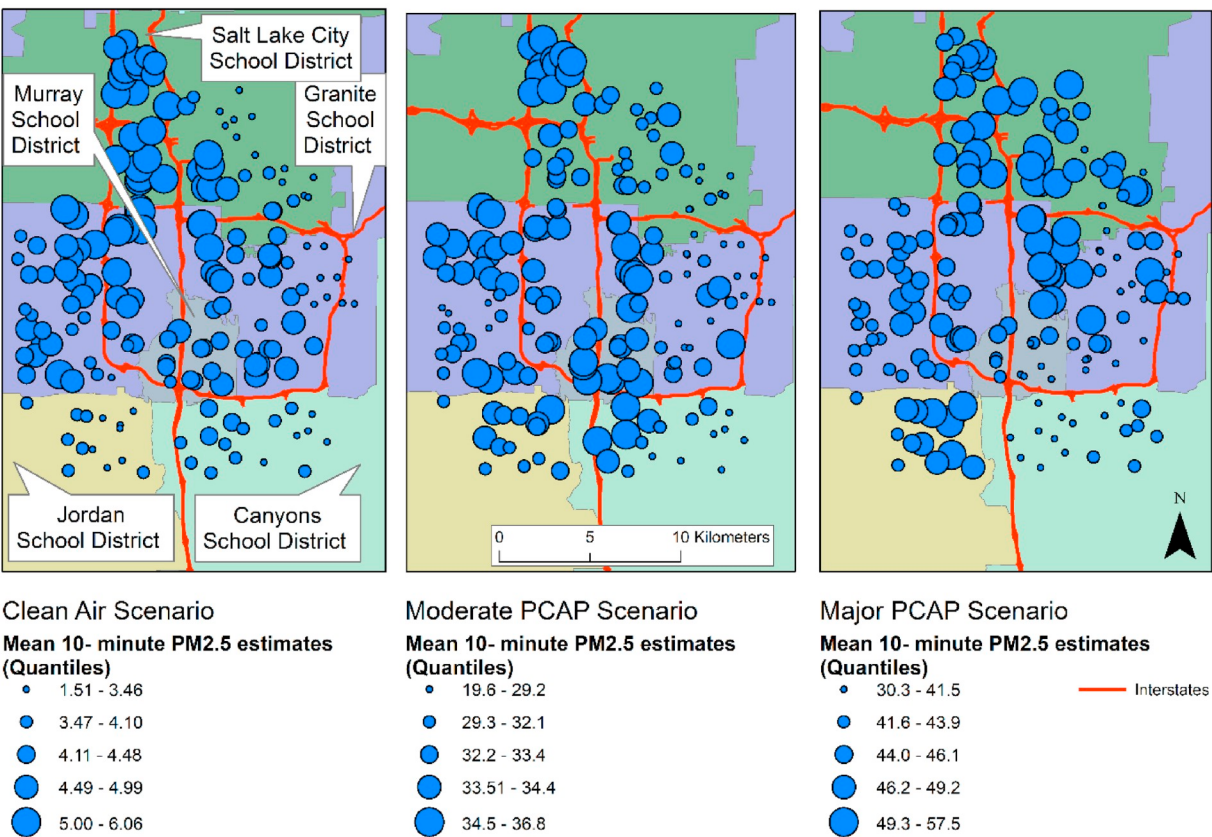


Fig. 2. Mean 10-min PM_{2.5} levels for each 48-h scenario at Salt Lake County public schools ($n = 174$).

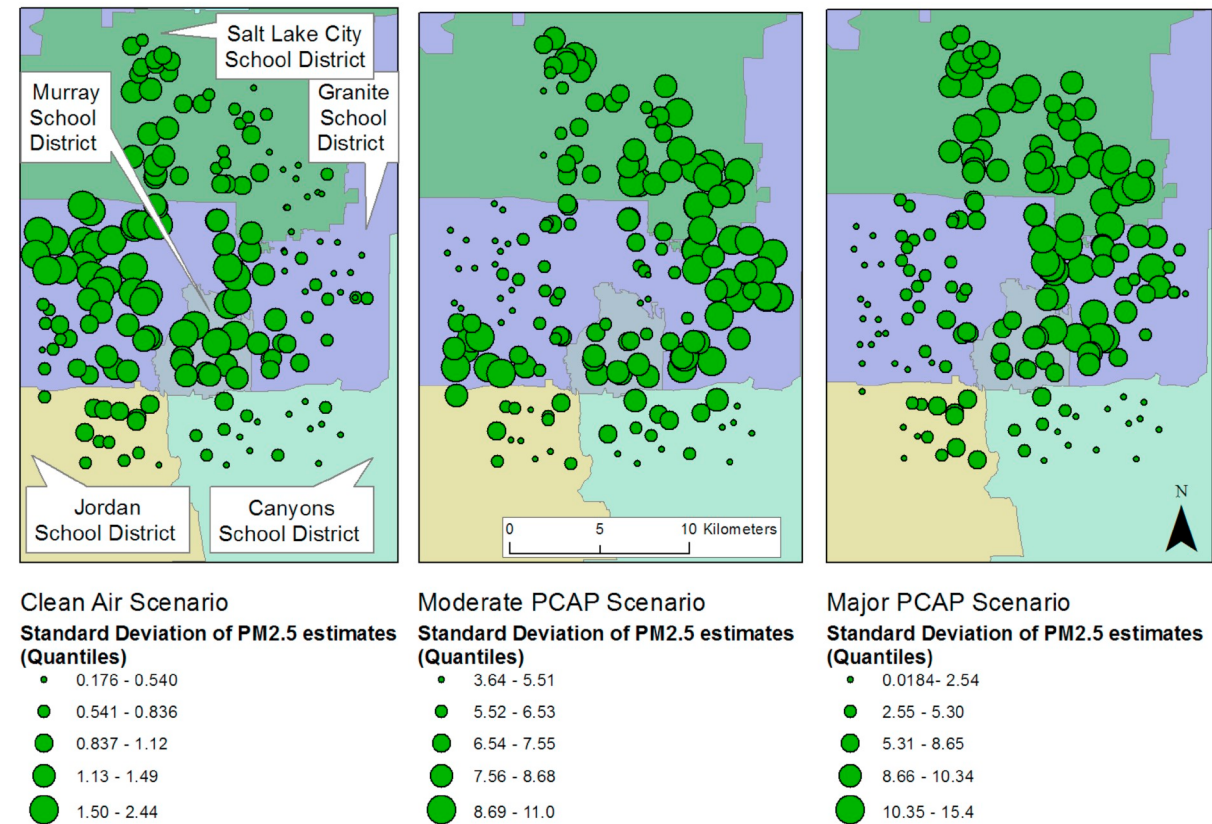


Fig. 3. Standard deviation of PM_{2.5} estimates at selected SLC public schools ($n = 174$) in the three scenarios.

Table 4
Results of GEEs predicting PM_{2.5} at Salt Lake County Public Schools (*n* = 174) under three different scenarios.

	Clean Air				Moderate PCAP				Major PCAP			
	Coeff.	Exp (Coeff.)	95% CIs	P	Coeff.	Exp (Coeff.)	95% CIs	p	Coeff.	Exp (Coeff.)	95% CIs	p
(Intercept)	1.416			< 0.001	3.458			< 0.001	3.793			< 0.001
% Hispanic	.109	1.115	1.093–1.137	< 0.001	.044	1.045	1.028–1.063	< 0.001	.019	1.019	1.011–1.026	< 0.001
% Non-Hispanic minority students	.037	1.038	1.009–1.067	0.010	.013	1.013	1.008–1.018	< 0.001	.020	1.020	1.008–1.033	0.001
Pop Density	-.030	0.970	.940–1.001	0.058	.005	1.005	.996–1.014	0.247	.011	1.011	1.005–1.017	0.001
Primary School	-.002	0.998	.940–1.059	0.946	.004	1.004	.995–1.012	0.366	-.010	0.991	.970–1.011	0.361
Charter School	.092	1.196	1.024–1.173	0.008	.027	1.028	1.020–1.035	< 0.001	.008	1.008	.973–1.045	0.658
Alt./Special Ed.	.082	1.086	1.024–1.173	< 0.001	.028	1.028	.988–1.070	0.174	.024	1.024	.982–1.069	0.266
Title I Eligible	.001	1.095	.916–1.095	0.975	.024	1.024	1.017–1.032	< 0.001	.010	1.010	.980–1.041	0.531

Note: Models use an inverse Gaussian distribution with a log link function, an exchangeable correlation matrix and school district clusters. Statistically significant *p*-values are highlighted in bold font. CI = confidence interval.

air scenario, schools with higher minority student composition were disproportionately exposed to higher concentrations. Specifically, at the school-level, a one standard deviation increase in the proportion of Hispanic students was associated with a 12% increase in concentration of PM_{2.5}, which is equivalent to a 0.55 µg/m³ increase. The effect size for percent non-Hispanic minority was smaller, at 4% (*p* = 0.010), equivalent to a 0.18 µg/m³ increase. Charter schools were exposed to concentrations of PM_{2.5} that were 20% higher than non-charter schools, indicating a 0.92 µg/m³ increase (*p* = 0.008), and alternative/special education schools had concentrations that were 9% higher than regular schools, equaling a 0.41 µg/m³ increase (*p* < 0.001).

When predicting PM_{2.5} concentrations during a moderate PCAP, schools with greater proportions of minority students had higher concentrations of PM_{2.5} exposure. When the proportion of Hispanic students was one standard deviation above the mean, PM_{2.5} concentrations were 5% higher (a 0.86 µg/m³ increase) than when that proportion was at the mean (*p* < 0.001). The increased exposure based on the proportion of non-Hispanic minority students was smaller, at 1%, indicating a 0.17 µg/m³ increase (*p* < 0.001). Charter schools had concentrations of PM_{2.5} that were 3% higher (equal to a 0.52 µg/m³ increase) than non-Charter schools (*p* < 0.001). Title I schools (schools serving low-income children) were also disproportionately exposed to higher PM_{2.5} concentrations during the moderate inversion. PM_{2.5} concentrations were 2% higher at Title I schools vs. non-Title I schools, equivalent to a 0.34 µg/m³ increase (*p* < 0.001).

During a major PCAP, PM_{2.5} exposure concentrations were higher for schools with greater proportions of minority students. When the proportions of Hispanic and non-Hispanic minority students were one standard deviation above the mean, PM_{2.5} concentrations were 2% (*p* < 0.001) and 2% (*p* = 0.001) higher, respectively, than when each variable was at the mean; a 2% increase in PM_{2.5} corresponds to a 0.54 µg/m³ increase. Lastly, in terms of the control variable, schools in neighborhoods with greater population density had higher concentrations of PM_{2.5} during the major inversion (*p* < 0.001).

As a sensitivity analysis, we predicted median PM_{2.5} values instead of the mean PM_{2.5} values reported in Table 4. The use of mean PM_{2.5} yielded identical results in terms of direction and significance (*p* < 0.05) to the median PM_{2.5} models. This indicates that findings were generally robust with respect to an alternative specification of the dependent variable.

4. Discussion

Improving upon Gaffron and Neimeier's (2015) bivariate analysis in California, our multivariate analysis findings reveal disparities in PM_{2.5} exposure based on the characteristics of schools and schoolchildren in SLC. Increases in several of the sociodemographic variables were associated with increased concentrations of PM_{2.5}. Even small increases in

PM_{2.5} can have important health effects. For example, relatively small increases in weekly exposure to PM_{2.5} (1 µg/m³) increases inhaler use by asthmatics by 0.82% (Williams et al., 2019).

The two racial/ethnic minority composition variables emerged as the most consistently significant indicators of disparate air pollution exposures under all three air pollution scenarios. Even during the relatively clean air scenario, we found that schools with higher proportions of minority students were exposed to higher levels of PM_{2.5} than schools with higher proportions of white students. The robustness of these racial/ethnic inequalities indicates a pattern of environmental injustice that aligns with the findings of previous studies of schools and/or schoolchildren (Kweon et al., 2018; Pastor et al., 2006; Chakraborty and Zandbergen, 2007; Grineski and Collins, 2018; Collins et al., 2019; Morello-Frosch et al., 2002; Gaffron, Neimeier, 2015). Note that we found evidence of racial/ethnic disparities in our models while controlling for the economic status of the school student body, which indicates that racial/ethnic minority student status was powerfully predictive of greater PM_{2.5} exposures independent of the economic status of students. The persistence of racial/ethnic disparities in our findings suggests that race/ethnicity shapes patterns of unequal air pollution exposure for schoolchildren within SLC. Our results indicating greater PM_{2.5} exposure for Title I eligible school status align with prior findings that schools serving economically deprived students were exposed to higher levels of pollution (Pastor et al., 2006; Grineski and Collins, 2018; Collins et al., 2019; Salvesen and Zambito, 2010), though this variable was only significant during the moderate PCAP.

Charter school status was associated with significantly higher PM_{2.5} in the relatively clean and moderate PCAP scenarios. Over the last 20 years, charter schools have come to serve a population that is increasingly Hispanic and Asian; enrollments are also on the rise (NCES, 2019). Nationally, charter schools also serve a disproportionately low-income population. Specifically (in Fall, 2016), 34% of students enrolled in charter schools attended high-poverty schools (i.e., schools with > 75% of students qualify for free or reduced-price meals), compared to 24% in traditional schools (NCES, 2019). Given that charter schools serve students who are more likely to be minority and of low income, this variable is important to future environmental justice studies of schools, and should be included in a national evaluation.

Our results indicate shifting patterns of injustice between the pollution scenarios. Table 5 provides a summary of significant findings, which allow the reader to examine how patterns shifted between each scenario. These findings shed light on the variability associated with air pollution exposure in SLC. The environmental injustice of air pollution exposure in this study emerged as an unstable phenomenon, with the exception of findings for race/ethnicity. Across the three scenarios, the two race/ethnicity variables are the only ones for which there were no changes in directionality or significance. The unchanging nature of those associations reveals how persistent those inequalities are in

Table 5
Summary chart comparing findings across 3 p.m._{2.5} Scenarios (based on Table 4).

Independent Variables	Clean Air	Moderate PCAP	Major PCAP
% Hispanic Students	{+}	{+}	{+}
% Non-Hispanic Minority Students	{+}	{+}	{+}
Population Density	-	+	{+}
Primary School	-	+	+
Charter School	{+}	{+}	+
Alternative/Special Education	{+}	+	+
Title I Eligible	+	{+}	+

Key: {+} Significant and positive association ($p < 0.05$) + Positive association, ($p > 0.05$) - Negative association ($p > 0.05$).

exposure to PM_{2.5}. This could be due to the role of residential segregation in increasing exposures to pollution, which has been documented in the US-based distributional environmental justice literature (Taylor, 2014). SLC was subject to segregated housing patterns that forced Hispanic and black minorities to cluster in specific residential areas within the urban core (Iber, 2000; Bringham, 1981). Those areas are located on the SLC valley floor at topographically low elevations, which are subject to relatively higher concentrations of PM pollution (Pope et al., 1999). Thus, racial segregation patterns across a steep elevation gradient could explain the robust associations of our racial/ethnic minority variables with increased PM_{2.5} exposures across all scenarios.

Our analysis of the major PCAP yielded the fewest statistically significant results. This suggests some dimensions of social disparity wash out when PM_{2.5} pollution is at its worst in SLC. Specifically, the findings for economic deprivation (i.e., Title 1) and charter school status, which were statistically significant predictors under moderate PCAP conditions, diminished in significance when PM_{2.5} was at its peak, adjusting for clustering and effects of other variables in the GEE.

Our study design has limitations. While the use of AQ&U data was a strength, it reduced the spatial extent of the study area to the central portion of SLC. The spatial extent excludes the far west side of the county where air quality and environmental justice issues are of concern. Our PM_{2.5} measurements pertain to 48-h in each pollution scenario. While we believe this timeframe was adequate for capturing differences in pollution scenarios in SLC, the potential exists that 48-h does not fully capture air pollution exposure during each scenario. In this case, we were not able to explore longer scenarios. Since we began collecting data in late 2017, there has been only one major PCAP event, and during that event, there was only one consecutive 2-day period with PM_{2.5} levels and meteorological conditions indicative of a severe PCAP (See Fig. S-7 in supplemental material).

While we accounted for variability between scenarios by using 48-h periods with similar low wind patterns and systematically demonstrated that patterns of environmental injustice varied, relatively clean air conditions occur under other types of weather conditions. It is also the case that PM_{2.5} can spike during high wind conditions or during forest fires. Future studies could explore a variety of scenarios and weather conditions, as our study was a first step in this line of research. In addition, our study does not fully capture children's exposure. Their school is not the only site of their air pollution exposure, and thus, we only assessed exposure disparities in one relevant location. We also lacked measures of air quality inside schools, and some schools are likely more porous than others, increasing exposures in some schools relative to others. While Table 5 portrays how the patterns of disparity varied among the three scenarios, future research is needed to examine the historical development of those patterns.

5. Conclusions

This study illustrates the value of community-university partnership

centered on air quality. Through a partnership between SLC residents and some co-authors of this study, We were able to utilize data from many PM_{2.5} sensors due to a partnership between SLC residents and the co-authors of this study. Had we relied on the Utah Division of Air Quality's air monitoring network, we would have been limited to two air monitors in our case study area, greatly limiting our ability to construct accurate air pollution surfaces in SLC's complex topography.

Disproportionate exposure in public schools based on race/ethnicity and socioeconomic status is concerning given that air pollution has negative impacts on children's health and academic performance (Kweon et al., 2018; McConnell et al., 2006; Wang et al., 2009; Butthumrung et al., 2008; Volk et al., 2011; Pastor et al., 2006; Mohai et al., 2011). Public schools are considered a governmental responsibility, and it is a federal policy that all children in the U.S. participate in the educational system (Grineski and Collins, 2018). Therefore, it should be the responsibility of the government to protect the well-being of children while they are attending public school in the U.S. The findings of our study speak to the importance of policy changes for protecting school-aged children from environmental harm in SLC and elsewhere.

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Human subjects

Not applicable.

Declaration of competing interest

Dr. Kelly and Dr. Gaillardon have financial interest in the company Tetrad: Sensor Network Solutions, LCC, which commercializes solutions for environmental monitoring.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2020.109543>.

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