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Spatial Analysis of Intra-Urban Air Pollution Disparities through an Environmental Justice Lens: A Case Study of Philadelphia, PA

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Abstract: Urban air pollution has been long understood as a critical threat to human health worldwide. Worsening urban air quality can cause increased rates of asthma, respiratory illnesses, and mortality. Air pollution is also an important environmental justice issue as it disproportionately burdens populations made vulnerable by their socioeconomic and health status. Using spatially continuous fine-scale air quality data for the city of Philadelphia, this study analyzed the relationship between two air pollutants: particulate matter ($PM_{2.5}$, black carbon (BC), and three dimensions of vulnerability: social (non-White population), economic (poverty), and health outcomes (asthma prevalence). Spatial autoregressive models outperformed Ordinary Least Squares (OLS) regression, indicating the importance of considering spatial autocorrelation in air pollution-related environmental-justice modeling efforts. Positive relationships were observed between $PM_{2.5}$ concentrations and the socioeconomic variables and asthma prevalence. Percent non-White population was a significant predictor of BC for all models, while percent poverty was shown to not be a significant predictor of BC in the best fitting model. Our findings underscore the presence of distributive environmental injustices, where marginalized communities may bear a disproportionate burden of air pollution within Philadelphia.

Keywords: air pollution; spatial modeling; $PM_{2.5}$; black carbon; environmental justice

1. Introduction

Globally, air pollution is a major environmental health hazard, especially in urban areas [1]. The World Health Organization (WHO) estimates that outdoor air pollution ($PM_{2.5}$ and ozone) caused 4.2 million premature deaths around the world in 2019 [2]. Currently, over half of the world's population resides in cities, but this is predicted to swell to 70% by 2050 due to the economic pressures of industrialization and globalization [3]. People living in cities face greater exposure to air pollution because of continued urban population growth, and consequently, these populations also face a greater risk of the negative effects of air pollution on human health and well-being [4].

$PM_{2.5}$, or particulate matter with an aerodynamic diameter less than or equal to 2.5 µm, is of great concern for urban areas such as Philadelphia, as it is primarily generated from anthropogenic actions such as industrial emissions, fossil fuel combustion, and gas-fueled vehicles [5]. Because of the small particle size, $PM_{2.5}$ can penetrate deep into the lungs, leading to increased incidence of asthma and other respiratory illnesses, as well as all-cause mortality rates [6,7]. As of 2024, the U.S. Environmental Protection Agency (EPA) has set their 24-h $PM_{2.5}$ standard at 35 µg/m^3 and their annual $PM_{2.5}$ standard at 9.0 µg/m^3 [8]. The WHO has set their 24-h $PM_{2.5}$ standard at 15 µg/m^3 and their annual $PM_{2.5}$ standard at 5 µg/m^3 [9]. As of 2021, 37.5 million Americans were living in counties with ambient concentrations of $PM_{2.5}$ above the acceptable levels set by the National Ambient Air Quality Standards (NAAQS). The American Lung Association reports fine particulate pollution (i.e., $PM_{2.5}$) as one of the most widespread and dangerous air pollutant along with ozone in its 2022 "State of the Air" report [10]. Black carbon (BC), also known as soot, is a subset of particles, mainly $PM_{2.5}$, that is especially detrimental to the environment and human health because of its warming capability and small size. BC is generated from incomplete fossil fuel combustion, which, in the United States, primarily is a consequence of vehicle emissions and household energy consumption [11]. Currently, there are no set standards on ambient BC concentrations in the U.S., although it is regulated indirectly through the $PM_{2.5}$ standards.

Air pollution is a pertinent issue for environmental justice advocates because it disproportionately burdens vulnerable populations based on race, ethnicity, and socioeconomic status [12,13]. Nationwide, people of color are 61% more likely than White people to live in a country with a failing grade for at least one air pollutant [10]. Some groups, such as children, the elderly, and low-socioeconomic status populations, have a greater risk for negative health outcomes from air pollution exposure [14–16] due to their limited capacity to cope with the effects of exposure. The social determinants of health, non-medical factors at the individual, community, and systemic level that shape the conditions of daily life, can compound health risk from air pollution exposure as people can face multiple layers of vulnerability. Vulnerability refers to both the negative socioeconomic and health consequences of exposure to an environmental hazard, as well as the ability of an individual or a group to cope and recover from the exposure [17]. In the case of air pollution, exposure is often ongoing, which means affected populations have limited strategies for coping with the air pollution on an individual scale, which can lead to feelings of helplessness [18]. Improving the understanding of the intersections of vulnerabilities like race, socioeconomic status, and health with air quality is crucial for fostering collective action to address environmental inequities and ensure justice.

While air pollution and environmental justice have been widely studied, research at the intra-city scale has been stymied due to insufficient fine-scale air pollution data. Several previous studies have relied on proxies, such as health outcomes [19] or proximity analysis [20], and spatially limited monitor-based air pollution observations [21]. However, air pollution in an urban context is highly variable due to the dynamic physical landscape of the city, meaning concentrations can vary dramatically over a short distance [22,23]. For example, Miller et al. found that differences in exposure to particulate matter across individual cities showed greater differences than overall exposure compared between cities [24]. Thus, fine-scale, citywide air pollution data are critical to illuminating the intra-urban implications of air pollution for environmental justice. Our group recently used a mobile monitoring approach to measure $PM_{2.5}$ and BC concentrations in the city of Philadelphia with Structure of Urban Landscapes (STURLA) classifications to interpolate citywide air pollution prediction models for $PM_{2.5}$ and BC [25]. This air pollution prediction model assigned air pollutant concentrations to 120 m^2 grid cells across the city, enabling citywide research and analysis. The main objective of this study is to use these fine-scale data to investigate the granular relationships between urban air pollution and environmental justice.

Studies show that accounting for spatial dependence in the data is important both in research on air pollution and environmental justice. Use of spatially autoregressive [26], geographically weighted [27] and land-use regression models [28] have been shown to improve the accuracy of air pollution estimates and reduce uncertainty. In the case of Shen et al., their model of air pollution across the European continent using spatially varying linear regression even outperformed machine learning methods [27]. There is also demonstrated utility of considering spatial dependence in models investigating air pollution exposure through an environmental justice lens [16,29–31]. Park et al. [32] suggests that the lack of consideration for spatial autocorrelation may have biased previous assessments of air pollution's influence on asthma risk and shows that dealing with spatial autocorrelation can create stronger asthma risk models.

This study aims to use spatially autoregressive modeling techniques to understand the intra-urban relationship between air pollution, specifically $PM_{2.5}$ and BC, and socioeconomic and health data across the city of Philadelphia, PA. Specifically, poverty, non-White populations, and asthma will be used to demonstrate the social, economic, and health dimensions of vulnerability, although we recognize that these variables do not encapsulate all of the complexities that make an individual or group vulnerable. This study utilizes 120-m city wide air pollution predictions in the City of Philadelphia from Cummings et al. [25]. We aggregated air pollution data to the block group scale to (a) assess the presence of spatial dependence in air pollution, socio-economic, and health data; (b) compare spatially autoregressive models to more commonly used ordinary least squares (OLS) regression; and (c) highlight intra urban disparities in air pollution exposure. Access to air pollution data at such a fine spatial scale is rare, and it creates a unique opportunity to assess the distributional injustice of air pollution within a city.

2. Method

2.1. Study Area

The study area for this analysis is the city of Philadelphia, Pennsylvania, located on the east coast of the United States between the Schuylkill and Delaware Rivers. Philadelphia is Pennsylvania's largest city, encompassing 367 km^2 of land with a population of 16,037,909 residents as of 2020 [33]. Philadelphia consists primarily of high-density development with a population density of 4609 people per square kilometer [33] and, as the population continues to grow, projections predict that the city will gain more dense urban development in the coming years [34]. The city's heavy industry is primarily located on the southern and eastern borders along the banks of the Delaware and Schuylkill rivers. In contrast, the northern and western areas contain many large parks and an overall greater presence of green space [35]. Motor vehicle emissions, construction, and industrial activities are major sources of air pollution for the city [36].

Philadelphia contains a significant presence of marginalized communities. 23.1% of the population of Philadelphia lives below the poverty line, making it one of the poorest cities in the United States [33]. As of 2020, the population comprised 41.4% Black, 39.3% White, 15.1% Hispanic or Latino, and 7.4% Asian peoples [33]. Policies such as redlining and urban renewal have made Philadelphia into one of the most segregated cities in the US [37]. Philadelphia has been identified as having the seventh-highest level of segregation between Black and White populations of all US cities [37]. White populations are most concentrated in South Philadelphia, Center City, and the surrounding suburbs, while Black communities are located in the Northern and Western areas of the city (Figure 1).

The American Lung Association (ALA) ranked Philadelphia 18th in year-round particle pollution in 2022 [10]. The ALA highlighted people of color and people experiencing poverty as groups facing significant air quality risk in Philadelphia County [38]. The city's poor air quality has translated into negative health outcomes for its residents. Childhood asthma prevalence in the city of Philadelphia is 21%, which is almost three times greater than the national prevalence of 5.8% as of 2021 [39]. The burden of disease caused by air pollution has disparate impacts on younger and older populations, as well as communities of color. For example, Black and Hispanic children are over four times more likely to be hospitalized for asthma-related complications than White children [40].

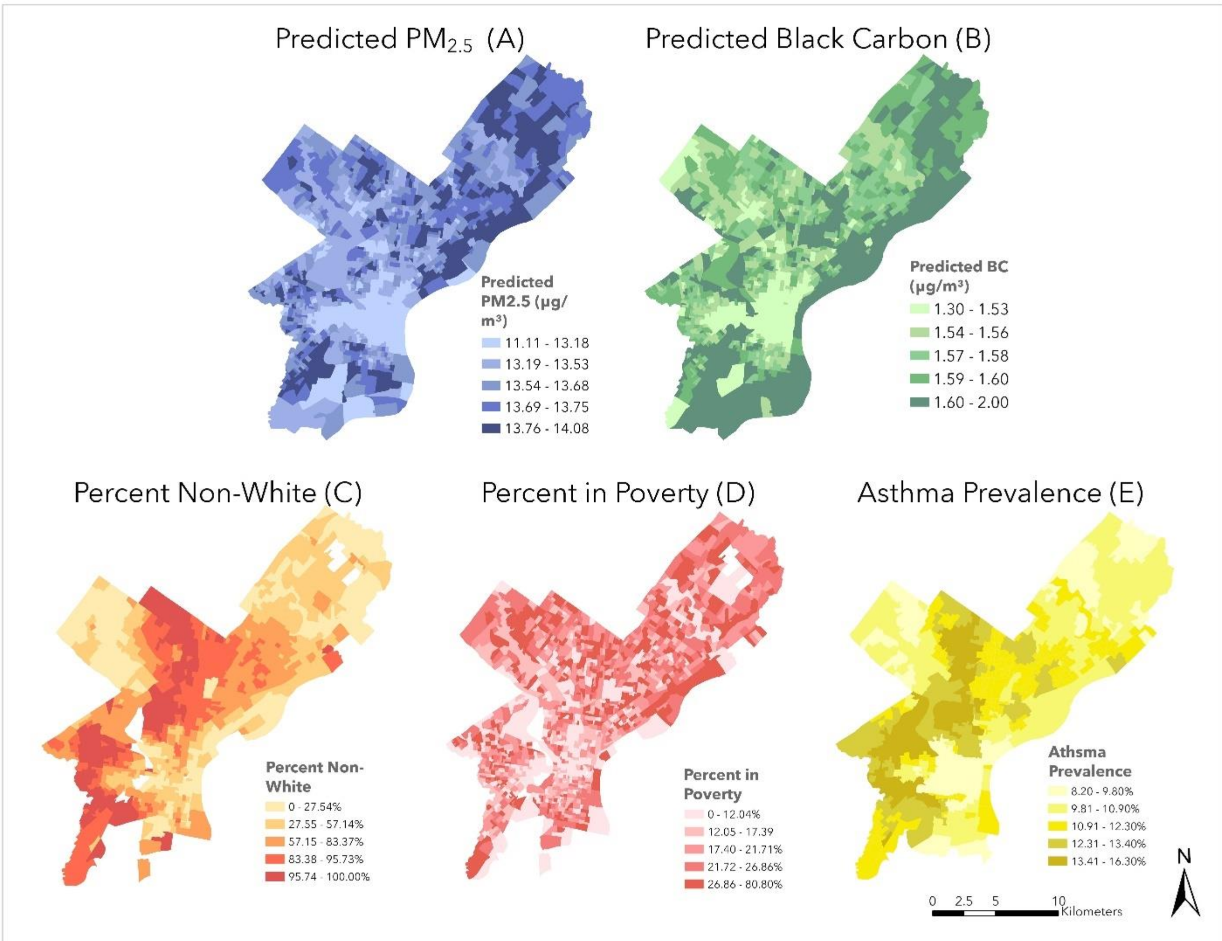

Figure 1. Average predicted $PM_{2.5}$ (μg/m^3) (**A**), average predicted BC (μg/m^3) (**B**), percent non-White (US Census) (**C**), percent in poverty (US Census) (**D**), and prevalence of asthma (CDC) (**E**) in Philadelphia, PA summarized in 120 m^2 grid cells across the city.

2.2. Data Source

This study focused on five variables in total with two representing air pollution exposure (predicted $PM_{2.5}$ and predicted BC) and three representing social, economic, and health vulnerabilities (percent non-White population, percent of population in poverty, and asthma prevalence in the population). This study employs fine-scale air pollution prediction from the work of Cummings et al. [25], which used a mobile monitoring method to collect $PM_{2.5}$ and BC concentrations [41] and Structure of Urban Landscapes (STURLA) classifications to interpolate citywide air pollution prediction models for $PM_{2.5}$ and BC [25]. The air pollution data were averaged for each block group within the study area to allow for spatially consistent analysis with the social, economic, and health variables (Figure 1).

Race and poverty data were downloaded from the U.S. Census Bureau [42,43]. Race data were obtained from the 2020 Decennial Census while the poverty data were sourced from the 2020 American Community Survey. Asthma data were downloaded from the 2019 Centers for Disease Control 500 Cities Project dataset for Philadelphia on the census tract level [44]. Block groups with no population were excluded from our analysis. Further, not all block groups contained data for asthma prevalence, so block groups without this data were excluded from the health models.

2.3. Geospatial Analysis

Socioeconomic, health, and air pollution data were mapped using ArcGIS Pro 3.2 to visualize their spatial distribution within the city (Figure 1). These data were imported into R Studio and assessed for spatial dependence using the Moran's I test. Spatial dependence refers to the relationship between a measured variable at neighboring locations. The Moran's I test measures spatial dependence through spatial autocorrelation. The test calculates a Moran's I value measuring how similar or dissimilar the data are at neighboring locations (Equation (1)) by comparing the standard deviations of each observation with the mean standard deviation of its neighbors weighted by their spatial relationships [45]. The Moran's I value ranges from −1 to 1 with negative values indicating negative spatial autocorrelations and dissimilarity among neighbors, and positive values indicating positive spatial autocorrelation and the presence of clustering.

$$I = \frac{n}{W} \frac{\sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (1)$$

where n is the number of observed locations, x_i and x_j are observations of the variable of interest at neighboring locations, $\bar{x}$ is the mean of the variable of interest at neighboring locations, W is the spatial weights matrix, and w_{ij} is the weight between I and j in the spatial weights matrix.

2.4. Statistical Analysis

To understand the relationships between the variables, univariate Ordinary Least Squares (OLS) regressions and univariate spatial autoregressive (spatial error, spatial lag) regressions were conducted in R Program ver 4.3. OLS is often used to quantify the relationship between a dependent variable and one or more independent variables by estimating the coefficients of a linear regression equation that captures the underlying relationship between the variables. As spatial dependence is present in the datasets, the foundational assumption of independence for linear regression is violated. Thus, spatial lag and spatial error models are employed, since they account for the spatial autocorrelation of the data. OLS analysis is conducted to provide a reference for the importance of considering spatial autocorrelation.

Univariate regression was purposely chosen to isolate the relationships between air pollution and vulnerability variables. Multicollinearity, particularly of the vulnerability variables, was of concern as it can lead to model overfitting and limits the interpretability of multiple regression models. Previous research has established the correlations between populations of color, poverty, and asthma [40,46–48]. For instance, in a nationwide study, Keet et al. [48] found that individual and neighborhood-level poverty, as well as Black racial identity, were associated with increased risk of asthma. Thus, multiple regression would be inappropriate, as we know from empirical research that the vulnerability variables are highly correlated.

In the Spatial Lag model, a new spatially lagged dependent variable is introduced to represent the spatial effects of the dependent variable in neighboring observations [49]. The model is expressed mathematically as:

$$y = pWy + X\beta + \epsilon \quad (2)$$

where y is the dependent variable, W is the spatial weights matrix, p is the coefficient to the spatial autocorrelation term which represents the strength of the spatial dependence, X is a matrix of observations on the explanatory variables, β is a vector of regression coefficients, and ϵ is the error term. The pWy term is the spatial lag term which captures spatial autocorrelation based on how much the value of y at a location is influenced by the neighboring location's y values.

In contrast to the Spatial Lag model's approach to capturing spatial autocorrelation as a dependent variable, the Spatial Error model accounts for spatial dependence through the model's error term [50]. In the error term, the error from each observation is correlated with the error from its neighboring observations as shown in Equation (3):

$$y = X\beta + \varepsilon$$
$$\varepsilon = \lambda W\varepsilon + \xi \quad (3)$$

where y is the dependent variable, X is a matrix of observations on the explanatory variables, β is a vector of regression coefficients, ε is the vector of error terms, spatially weighted using the weights matric (W), λ is the Spatial Error coefficient, and ξ is a vector of independent identically distributed error terms. This model is most useful when the spatial dependence in the data is caused by factors not included in the model.

For the socio-economic factors, air pollution served as the dependent variable, while the socioeconomic data served as independent variables. For the relationship with asthma prevalence, the air pollutants were independent variables, since outdoor air pollution has a well-documented causal relationship with asthma [51,52].

3. Results

The results of Moran's I tests (Table 1) indicate that spatial dependence is present at some magnitude in all the datasets used in this analysis. The test shows high levels of spatial autocorrelation in $PM_{2.5}$ and BC predictions, as well as % non-White and asthma prevalence. Spatial autocorrelation was assessed at the block group scale for all variables.

Table 1. Summary of global Moran's I statistic for each variable.

Variable	Moran's I	*p*-Value
Predicted $PM_{2.5}$	0.78	$<2.2 \times 10^{-16}$
Predicted BC	0.68	$<2.2 \times 10^{-16}$
Percent in Poverty	0.15	$<2.2 \times 10^{-16}$
Percent Non-White	0.85	$<2.2 \times 10^{-16}$
Asthma Prevalence	0.87	$<2.2 \times 10^{-16}$

Comparisons of the results of OLS and spatially autoregressive models are shown in Tables 2–4 for the socioeconomic and health variables. In all cases, the spatial autoregressive models had higher r-squared values than the OLS model, indicating the importance of accounting for spatial dependence in terms of model performance.

Results differed for $PM_{2.5}$ and BC models. Specifically, the Spatial Error model performed best in terms of both r-squared and AIC for evaluating the relationships between $PM_{2.5}$ and percent in poverty and percent non-White. Given that the distribution of air pollution is related to but not completely caused by socio-economic variables, this model's strong performance, especially in comparison to the Spatial Lag model, is to be expected. However, in the case of BC, although the Spatial Error models had higher r-squared and lower AIC than the Spatial Lag models, the *p*-values of the regression coefficient in the spatial error models were not significant for the poverty and asthma models. This indicates that there is not sufficient evidence to reject the null hypothesis that the coefficient is equal to zero. Thus, there is not definitive evidence of an association with BC for these specific Spatial Error models and the model results are insignificant. This may be due to spatial heterogeneity in relationship, meaning that the relationship between the vulnerability variables and BC varies across space, thus requiring more complex models to accurately discern this. However, the *p*-value of the Spatial Error model assessing the relationship between BC and non-White population was less than 0.05, indicating a significant relationship between the two variables.

When accounting for spatial autocorrelation in the residuals, there is a strong relationship between $PM_{2.5}$ concentrations and the socioeconomic variables (Tables 2 and 3). The r-squared values for the percent non-White and percent in poverty Spatial Error models were both 0.85. This is much greater than the r-squared values calculated for the OLS (percent non-White = 0.11 and percent in poverty = 0.13) and Spatial Lag (percent non-White = 0.60 and percent in poverty = 0.57) models. Further, both variables' models showed low AIC values (−313.232 for non-White and −306.48 for poverty) in comparison with OLS AIC values (1687.62 for non-White and 1668.99 for poverty), demonstrating the strong fit of the Spatial Error model. The Spatial Error model results show there is a small positive relationship between $PM_{2.5}$ and both percent non-White (regression coefficient = 0.002) and percent in poverty (regression coefficient = 0.001) for $p \leq 0.05$. Overall, all coefficients reflect a small magnitude positive association between socioeconomic variables and $PM_{2.5}$. The Spatial Error coefficient was equal to 0.94 in both variables' models, indicating a high level of spatial dependence in their residuals. The Breusch-Pagan test shows the presence of heteroskedasticity in all models, which is to be expected given the spatial dependence present in the residuals.

Table 2. The percent of non-White population correlated with $PM_{2.5}$ and BC concentrations at the census block group level.

	$PM_{2.5}$			BC		
	OLS	**Spatial Lag**	**Spatial Error**	**OLS**	**Spatial Lag**	**Spatial Error**
Variables						
Coefficient	0.006	0.003	0.002	0.0005	0.0003	0.0004
p-Value	0.0004 ***	0 ***	0 ***	0 ***	0 ***	0.00001 ***
Spatial Lag Effects	-	0.57	-	-	0.50	-
p-Value	-	0 ***	-	-	0 ***	-
Spatial Error Effects	-	-	0.94	-	-	0.85
p-Value	-	-	0 ***	-	-	0 ***
Measures of Fit						
R-Squared	0.11	0.60	0.85	0.06	0.40	0.70
Standard Error	0.46	0.31	0.18	0.07	0.05	0.04
AIC	1687.62	750.88	−313.232	−3413.31	−3930.39	−4700.06
Log Likelihood	−841.811	−372.44	−158.62	1708.66	1968.2	2352.03
Breusch-Pagan Test	377.79	1212.58	16.37	290.67	113.00	65.21
p-Value	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***

Note: When *p*-values were given, the value is indicated by the following significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', and $p \leq 0.05$ '*'.

Table 3. The percent of population in poverty correlated with $PM_{2.5}$ and BC concentrations at the census block group level.

	$PM_{2.5}$			BC		
	OLS	**Spatial Lag**	**Spatial Error**	**OLS**	**Spatial Lag**	**Spatial Error**
Variables						
Coefficient	0.017	0.007	0.001	0.002	0.0008	0.00094
p-Value	0 ***	0 ***	0.03 *	0 ***	0 ***	0.69
Spatial Lag Effects	-	0.57	-	-	0.50	-
p-Value	-	0 ***	-	-	0 ***	-
Spatial Error Effects	-	-	0.94	-	-	0.86
p-Value	-	-	0 ***	-	-	0 ***
Measures of Fit						
R-Squared	0.13	0.57	0.85	0.06	0.50	0.70
Standard Error	0.46	0.31	0.19	0.07	0.05	0.04
AIC	1668.99	762.28	−306.48	−3418.33	−3916.27	−4680.94
Log Likelihood	−32.50	−378.14	155.24	1711.17	1961.13	2342.47
Breusch-Pagan Test	84.79	195.42	35.34	114.67	197.10	46.98
p-Value	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***

Note: When *p*-values were given, the value is indicated by the following significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', and $p \leq 0.05$ '*'.

The Spatial Lag models outperformed other models when assessing the relationship between asthma and the air pollutants (Table 4). The Spatial Lag model had an r-squared value of 0.88 and an AIC of 2788.12 for $PM_{2.5}$ and an r-squared value of 0.88 and an AIC of 2796.51 for BC. This is far greater than the r-squared of 0.18 and far less than the AIC of 5065.48 for the $PM_{2.5}$ OLS model and the r-squared of 0.09 and far less than the AIC of 5179.95 for the BC OLS model, indicating a stronger fit for the spatially autoregressive model. While the Spatial Error models had high r-squared and AIC values, the *p*-values of the regression coefficients were not significant, and there is insufficient evidence to conclude that the air pollution variables have a significant effect on asthma prevalence. The Spatial Error models produced smaller regression coefficients than the other models, which may mean its effect is hard to detect (Supplemental Figures S1–S3). Nevertheless, in both Spatial Lag models, there is a positive relationship between the air pollutants and asthma prevalence, although the coefficients were relatively small. The regression coefficient is 0.45 for the $PM_{2.5}$ model and 0.69 for the BC model for $p \leq 0.05$. In contrast with the $PM_{2.5}$, the *p*-values of the Breusch-Pagan test for the PC spatial models were greater than 0.05, indicating there is not a significant level of heteroskedasticity in the models. This test reveals that there is relatively consistent variability in the residuals of these models, an important consideration for regression performance and reliability.

Table 4. $PM_{2.5}$ and BC concentrations correlated with asthma prevalence at the census block group level.

	$PM_{2.5}$			**BC**		
	OLS	**Spatial Lag**	**Spatial Error**	**OLS**	**Spatial Lag**	**Spatial Error**
Variables						
Coefficient	1.62	0.45	0.12	7.63	0.69	0.17
p-Value	0 ***	0 ***	0.14	0 ***	0.004 ***	0.707
Spatial Lag Effects	-	0.79	-	-	0.945	-
p-Value	-	0 ***	-	-	0 ***	-
Spatial Error Effects	-	-	0.95	-	-	0.95
p-Value	-	-	0 ***	-	-	0 ***
Measures of Fit						
R-Squared	0.17	0.88	0.88	0.09	0.88	0.88
Standard Error	1.63	0.61	0.61	1.70	0.70	0.61
AIC	5065.48	2788.12	2800.5	5179.95	2796.51	2802.51
Log Likelihood	−2530.74	−1391.06	−1398.25	−2587.98	−1395.26	−1399.25
Breusch-Pagan Test	4.33	11.05	14.13	13.13	0.25	0.0059
p-Value	0.04	0.0009 ***	0.0002 ***	0.0003 ***	0.62	0.94

Note: When *p*-values were given, the value is indicated by the following significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', and $p \leq 0.05$ '*'.

4. Discussion

This research aims to investigate how socio-economic and health vulnerabilities intersect with air pollution in Philadelphia. Overall, accounting for spatial dependence in any capacity through the use of either Spatial Lag or Spatial Error models improved model performance when compared to the OLS model. This finding is consistent with previous studies' findings that also emphasize the importance of spatial autocorrelation in environmental justice analyses [16,30,31]. Positive relationships were found between $PM_{2.5}$ and the socioeconomic variables tested when accounting for spatial dependence in the residuals using the Spatial Error model. In effect, higher concentrations of $PM_{2.5}$ are associated with higher percentages of the population living in poverty and being non-White. Higher asthma prevalence was associated with greater $PM_{2.5}$ and BC concentrations for the Spatial Lag models (r-squared = 0.88), while the regression coefficients of the Spatial Error models (r-squared = 0.88) did not have significant *p*-values, despite also having a high r squared value. It should be noted, however, that in both the socioeconomic and health models, the significant regression coefficients were small.

Previous work has shown air pollution exposure varies across the United States for socioeconomic population subgroups [53–55]. Our results are consistent with these studies in finding that populations living in census block groups with greater proportions of people of color and living in poverty face greater exposure to $PM_{2.5}$ [53–56]. Modeled air quality data are commonly used to provide the spatially continuous air quality data needed to investigate spatial inequities [20,55,56]. For example, Bravo et al. and Collins et al. both conducted their analysis using EPA air pollution data and the Downscaler methods to create air quality data for the United States.These methods yield 12 × 12 km predictions, which are too coarse for meaningful urban analysis [55,56]. Maroko used air dispersion modeling to model $PM_{2.5}$ for the 733,517 populated tax lots across New York City, NY, to show heightened exposure for Latinx and poorer populations within the Bronx and Brooklyn [20]. Although their results did not show significant city-wide exposure inequities, the air dispersion modeling used by Maroko only accounts for $PM_{2.5}$ from local stationary sources, meaning their results do not include transportation emissions, which account for a large portion of urban air pollution [20,57].

Our study showed statistically significant relationships between BC and percent non-White as well as asthma prevalence, although the regression coefficients were small. While the OLS and Spatial Lag models for percent poverty had statistically significant regression coefficients, their low r-squared values indicate that the models do not fully explain BC distribution. The Spatial Error model had a much higher r-squared value of 0.70 although the regression coefficient was not statistically significant. BC emissions are a product of the incomplete combustion of carbon-based fuels most often used to power diesel engines in transportation vehicles [58] and heavy machinery [59]. BC can also originate from other anthropogenic and natural sources such as waste burning [60] and wildfires [61]. As seen in Figure 1, concentrations of BC are greatest along the eastern border of the city where Interstate-95 runs, a major highway that connects much of the east coast of the United States. I-95 serves as a critical transportation linkage between Philadelphia and New York City, and the portion that runs through Center City Philadelphia sees on average 160,000 vehicles a day, including many large trucks that run on diesel [62]. Most of the block groups adjacent to the highway are sparsely populated, since they are primarily used for industrial purposes which may have impacted the BC models.

While there are many environmental justice studies that look at $PM_{2.5}$ as a whole, there are few that specifically investigate ambient BC despite its deleterious effects on public health and environmental quality [63–65]. Our study found a positive relationship between the percentage of people of color living in a census block group and BC concentrations. This is in line with previous studies that show how living in a neighborhood with a greater proportion of non-White population is positively correlated with increased BC exposure [66–68]. For example, Northcross et al. conducted a case study that measured higher concentrations of BC and $PM_{2.5}$ in Ivy City, a historically Black neighborhood of Washington D.C., when compared with the rest of the city [67]. Their study presents evidence that the city's current air monitoring network was not accurately capturing the burden of air pollution faced by the neighborhood with vulnerable populations and prevented a previously approved parking lot from being constructed. Our and Northcross et al.'s studies show the power of accurate pollution data to reveal inequalities and reparative policies and actions.

In cities with documented segregations such as Philadelphia [69], where variations in the urban landscape can be scars of discriminatory development practices, it is especially critical to understand the social implications of intra-city variability in hazardous air pollution exposure. While the distributional injustice of air pollution has been widely studied [70,71], there have been difficulties finding empirical evidence of this pattern at the intra-city scale due to a lack of fine-scale air pollution data [20,72]. This research is unique to previous work in that we used spatially autoregressive models and finer-scale air pollution data (census block group). Air pollution is not spatially independent due to the complex and overlapping interactions of emission sources, atmospheric processes, topography, meteorologic conditions, and other geographic factors that affect its distribution. Thus, using OLS to study air pollution is inappropriate, as the foundational assumption of independence is violated. In this study, spatial autoregressive models were used to account for air pollution's spatial dependence and improve model strength. It is also important to study air pollution at the finest scale possible, since concentrations can vary dramatically over a small geographic area due to many of the same temporal and geographic factors that induce its spatial dependence. These small-scale variations become more prevalent in an urban environment where the composition and topography of the landscape are highly varied and there are many possible sources of pollution present [22,73].

Association of air pollution exposure with non-White and poor populations highlights a significant environmental justice problem for the city of Philadelphia. This association represents an instance of distributive injustice where neighborhoods that have higher concentrations of poverty and people of color are saddled with a greater air pollution burden than the rest of the city. The regression coefficients of our models were, in almost all cases, very small. Nevertheless, over the course of a lifetime, even small magnitude differences in air pollution exposure can have negative consequences for health and well-being. Weichenthal et al. found that $PM_{2.5}$ still has a significant impact on mortality even at very low concentrations (<5 μg/m^3), estimating that around 1.5 million deaths annually can be attributed to low level $PM_{2.5}$ [74]. As $PM_{2.5}$ concentrations used in this study ranged from 11.11 to 14.08 μg/m^3, small-scale differences of concentrations in tracks with varying levels of vulnerability can have significant impacts on the population's quality of life and overall well-being.

Previous studies in the city of Philadelphia have documented many other cases of distributive environmental injustices from heat exposure [75] to tree canopy cover [76] to access to high-quality parks [77]. Taken together, these injustices have a compounding effect, causing the continued reproduction of systemic inequities and negative consequences for the people living in these communities. For example, proximity to a point source pollution can affect home prices in an area, preventing members from being able to sell their homes and relocate away from harm and making the community less desirable for outside investment [78]. In effect, the relationships identified in this study serve to further demonstrate the spatially dependent environmental inequities that exist within the city and provide quantifiable evidence of the need for transformative actions.

5. Uncertainties and Limitations

The citywide air pollution dataset in this study is a modeled dataset carrying inherent limitations. The modeled dataset from Cummings et al. [25] is based on air pollution data that were collected through mobile monitoring over 12 days (6 replications) and driven on a 483 km (300 mile) route with the sensors mounted to a vehicle roof. The authors acknowledge that limiting their data collection to roadways may have introduced a layer bias into their results. Although their air pollution observations were greater than those collected at stationary EPA stations, both measurements captured similar patterns [25]. Further limitations to this data include the fact that air quality was only measured during the summer, that there were only six sampling repetitions at each location, and that the measurements were collected at different times throughout the day, rather than at the same time. $PM_{2.5}$ and BC concentrations vary seasonally and diurnally based on changes in meteorological conditions and anthropogenic activity [79]. A dense network of quality-controlled air pollution monitoring stations may be needed to create a more accurate representation of fine-scale air pollution distribution across the city [80].

This study was limited in that it only investigated two types of air pollution ($PM_{2.5}$ and BC) and three vulnerability variables (percent non-White, percent poverty, and asthma prevalence). Philadelphia also experiences elevated levels of other pollutants, such as ozone. The publicly available air quality data (airnow.gov (accessed on 11 June 2024)) show several days exceeding the national ambient ozone standard level in Philadelphia [81]. Vulnerability is nuanced, and we recognize that these three variables do not fully capture the many intersecting physical, social, economic, and health interactions that contribute to an individual or group's overall vulnerability. Due to concerns over multicollinearity, we refrained from conducting multiple regression analysis inhibiting our ability to understand the interaction effects of the chosen vulnerability variables. Future research should seek to expand the breadth and amount of vulnerability-related variables they investigate, and attempt to understand their interacting effects.

6. Conclusions

This study investigates the intersection of socio-economic and health vulnerabilities with air pollution in Philadelphia. Through the use of spatial autoregressive models and finer-scale air pollution data, we reveal spatial patterns of environmental disparity within the city. Our findings highlight the disproportionate burden of air pollution borne by vulnerable communities, particularly those characterized by higher percentages of poverty and non-White populations. The significance of spatial dependence in our models underscores the complexity of air pollution distribution and emphasizes the importance of accounting for spatial autocorrelation in environmental justice analyses. By revealing the spatially dependent nature of environmental inequities, our research contributes to a deeper understanding of intra-city variability in hazardous air pollution exposure. Despite the small magnitude of regression coefficients, the health implications of even minor disparities in air pollution exposure cannot be overlooked. These findings underscore the urgent need for transformative actions to address environmental injustices in Philadelphia and beyond. Implementing policies and interventions that prioritize the well-being of vulnerable communities is essential for promoting environmental equity and ensuring a healthier future for all residents. Future research should aim to expand the breadth of vulnerability-related variables investigated and explore their interacting effects. Additionally, efforts to improve the accuracy of air pollution models and coverage of air pollution monitoring networks to capture intra-urban variability are critical for developing a more comprehensive understanding of fine-scale air pollution distribution and its impacts on public health and environmental quality in urban areas, especially in vulnerable communities.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos15070755/s1, Figure S1: Graphs comparing observed PM2.5 and BC concentrations with those modeled using OLS, Spatial Lag (SLag) and Spatial Error (SpErr) models and percent poverty, Figure S2: Graphs comparing observed PM2.5 and BC concentrations with those modeled using OLS, Spatial Lag (SLag) and Spatial Error (SpErr) models and percent nonwhite, Figure S3: Graphs comparing observed asthma prevalence with those modeled using OLS, Spatial Lag (SLag) and Spatial Error (SpErr) models and PM2.5 or BC concentrations.

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References

1. Huang, J.; Pan, X.; Guo, X.; Li, G. Impacts of air pollution wave on years of life lost: A crucial way to communicate the health risks of air pollution to the public. *Environ. Int.* **2018**, *113*, 42–49. https://doi.org/10.1016/j.envint.2018.01.022.
2. World Health Organization. Ambient (Outdoor) Air Pollution. Available online: https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health (accessed on 23 April 2024).
3. Urban Development Overview. 2023. Available online: https://www.worldbank.org/en/topic/urbandevelopment/overview (accessed on 23 April 2024).
4. Strosnider, H.; Kennedy, C.; Monti, M.; Yip, F. Rural and Urban Differences in Air Quality, 2008–2012, and Community Drinking Water Quality, 2010–2015—United States. *MMWR Surveill. Summ.* **2017**, *66*, 1–10. https://doi.org/10.15585/mmwr.ss6613a1.
5. Huang, C.; Liu, K.; Zhou, L. Spatio-temporal trends and influencing factors of PM2.5 concentrations in urban agglomerations in China between 2000 and 2016. *Environ. Sci. Pollut. Res.* **2021**, *28*, 10988–11000. https://doi.org/10.1007/s11356-020-11357-z.
6. Anenberg, S.C.; Weinberger, K.R.; Roman, H.; Neumann, J.E.; Crimmins, A.; Fann, N.; Martinich, J.; Kinney, P.L. Impacts of oak pollen on allergic asthma in the United States and potential influence of future climate change. *GeoHealth* **2017**, *1*, 80–92. https://doi.org/10.1002/2017GH000055.
7. Feng, S.; Gao, D.; Liao, F.; Zhou, F.; Wang, X. The health effects of ambient PM2.5 and potential mechanisms. *Ecotoxicol. Environ. Saf.* **2016**, *128*, 67–74. https://doi.org/10.1016/j.ecoenv.2016.01.030.
8. EPA. Final Rule to Strengthen the National Air Quality Health Standard for Particulate Matter. 2024. Available online: https://www.epa.gov/system/files/documents/2024-02/pm-naaqs-overview.pdf (accessed on 11 June 2024).
9. World Health Organization. *WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; World Health Organization: Geneva, Switzerland, 2021; ISBN: 9789240034228. Available online: https://www.who.int/publications/i/item/9789240034228 (accessed on 23 April 2024).
10. American Lung Association State of the Air. Most Polluted Cities. 2022. Available online: https://www.lung.org/research/sota/city-rankings/most-polluted-cities (accessed on 23 April 2023).
11. Cho, R. The Damaging Effects of Black Carbon. In *State of the Planet*; Columbia Climate School: New York, NY, USA, 2016. Available online: https://news.climate.columbia.edu/2016/03/22/the-damaging-effects-of-black-carbon/ (accessed on 23 April 2023).
12. Gray, S.C.; Edwards, S.E.; Miranda, M.L. Race, socioeconomic status, and air pollution exposure in North Carolina. *Environ. Res.* **2013**, *126*, 152–158. https://doi.org/10.1016/j.envres.2013.06.005.
13. Perlin, S.A.; Wong, D.; Sexton, K. Residential Proximity to Industrial Sources of Air Pollution: Interrelationships among Race, Poverty, and Age. *J. Air Waste Manag. Assoc.* **2001**, *51*, 406–421. https://doi.org/10.1080/10473289.2001.10464271.
14. Qian, D.; Yan, W.; Antonella, Z.; Yun, W.; Petros, K.; Christine, C.; Francesca, D.; Schwartz, J.D. Air Pollution and Mortality in the Medicare Population. *N. Engl. J. Med.* **2017**, *376*, 2513–2522. https://doi.org/10.1056/NEJMoa1702747.
15. Sacks, J.D.; Stanek, L.W.; Luben, T.J.; Johns, D.O.; Buckley, B.J.; Brown, J.S.; Ross, M. Particulate Matter–Induced Health Effects: Who Is Susceptible? *Environ. Health Perspect.* **2011**, *119*, 446–454. https://doi.org/10.1289/ehp.1002255.
16. Pope, R.; Wu, J.; Boone, C. Spatial patterns of air pollutants and social groups: A distributive environmental justice study in the phoenix metropolitan region of USA. *Environ. Manag.* **2016**, *58*, 753–766. https://doi.org/10.1007/s00267-016-0741-z.
17. Horton, A.; Jones, S.J.; Brunt, H. Air pollution and public health vulnerabilities, susceptibilities and inequalities in Wales, UK. *J. Public Health* **2023**, *45*, 432–441. https://doi.org/10.1093/pubmed/fdac083.
18. Johnson, T.; Mol, A.P.J.; Zhang, L.; Yang, S. Living under the dome: Individual strategies against air pollution in Beijing. *Habitat Int.* **2017**, *59*, 110–117. https://doi.org/10.1016/j.habitatint.2016.11.014.
19. Conway, M. Mapping Social Vulnerability to Air Pollution in Philadelphia, PA. *Veritas Villanova Res. J.* **2020**, *2*, 122–130. Available online: https://par.nsf.gov/biblio/10286921-mapping-social-vulnerability-air-pollution-philadelphia-pa (accessed on 23 May 2023).
20. Maroko, A.R. Using air dispersion modeling and proximity analysis to assess chronic exposure to fine particulate matter and environmental justice in New York City. *Appl. Geogr.* **2012**, *34*, 533–547. https://doi.org/10.1016/j.apgeog.2012.02.005.
21. Gardner-Frolick, R.; Boyd, D.; Giang, A. Selecting Data Analytic and Modeling Methods to Support Air Pollution and Environmental Justice Investigations: A Critical Review and Guidance Framework. *Environ. Sci. Technol.* **2022**, *56*, 2843–2860. https://doi.org/10.1021/acs.est.1c01739.
22. Li, C.; Wang, Z.; Li, B.; Peng, Z.-R.; Fu, Q. Investigating the relationship between air pollution variation and urban form. *Build. Environ.* **2019**, *147*, 559–568. https://doi.org/10.1016/j.buildenv.2018.06.038.
23. Shakya, K.M.; Kremer, P.; Henderson, K.; McMahon, M.; Peltier, R.E.; Bromberg, S.; Stewart, J. Mobile monitoring of air and noise pollution in Philadelphia neighborhoods during summer 2017. *Environ. Pollut.* **2019**, *255*, 113195. https://doi.org/10.1016/j.envpol.2019.113195.
24. Miller, K.A.; Siscovick, D.S.; Sheppard, L.; Shepherd, K.; Sullivan, J.H.; Anderson, G.L.; Kaufman, J.D. Long-Term Exposure to Air Pollution and Incidence of Cardiovascular Events in Women. *N. Engl. J. Med.* **2007**, *356*, 447–458. https://doi.org/10.1056/NEJMoa054409.

25. Cummings, L.E.; Stewart, J.D.; Kremer, P.; Shakya, K.M. Predicting citywide distribution of air pollution using mobile monitoring and three-dimensional urban structure. *Sustain. Cities Soc.* **2022**, *76*, 103510. https://doi.org/10.1016/j.scs.2021.103510.
26. Kanaroglou, P.S.; Adams, M.D.; De Luca, P.F.; Corr, D.; Sohel, N. Estimation of sulfur dioxide air pollution concentrations with a spatial autoregressive model. *Atmos. Environ.* **2013**, *79*, 421–427. https://doi.org/10.1016/j.atmosenv.2013.07.014.
27. Shen, Y.; de Hoogh, K.; Schmitz, O.; Clinton, N.; Tuxen-Bettman, K.; Brandt, J.; Christensen, J.H.; Frohn, L.M.; Geels, C.; Karssenberg, D.; et al. Europe-wide air pollution modeling from 2000 to 2019 using geographically weighted regression. *Environ. Int.* **2022**, *168*, 107485. https://doi.org/10.1016/j.envint.2022.107485.
28. Bertazzon, S.; Johnson, M.; Eccles, K.; Kaplan, G.G. Accounting for spatial effects in land use regression for urban air pollution modeling. *Spat. Spatio-Temporal Epidemiol.* **2015**, *14–15*, 9–21. https://doi.org/10.1016/j.sste.2015.06.002.
29. Havard, S.; Deguen, S.; Zmirou-Navier, D.; Schillinger, C.; Bard, D. Traffic-Related Air Pollution and Socioeconomic Status: A Spatial Autocorrelation Study to Assess Environmental Equity on a Small-Area Scale. *Epidemiology* **2009**, *20*, 223–230. https://doi.org/10.1097/EDE.0b013e31819464e1.
30. Verbeek, T. Unequal residential exposure to air pollution and noise: A geospatial environmental justice analysis for Ghent, Belgium. *SSM—Popul. Health* **2019**, *7*, 100340. https://doi.org/10.1016/j.ssmph.2018.100340.
31. Jerrett, M.; Burnett, R.T.; Kanaroglou, P.; Eyles, J.; Finkelstein, N.; Giovis, C.; Brook, J.R. A GIS–Environmental Justice Analysis of Particulate Air Pollution in Hamilton, Canada. *Environ. Plan. Econ. Space* **2001**, *33*, 955–973. https://doi.org/10.1068/a33137.
32. Park, Y.; Kim, S.H.; Kim, S.P.; Ryu, J.; Yi, J.; Kim, J.Y.; Yoon, H.-J. Spatial autocorrelation may bias the risk estimation: An application of eigenvector spatial filtering on the risk of air pollutant on asthma. *Sci. Total Environ.* **2022**, *843*, 157053. https://doi.org/10.1016/j.scitotenv.2022.157053.
33. U.S. Census Bureau. QuickFacts: Philadelphia City, Pennsylvania. 2022. Available online: https://www.census.gov/quickfacts/philadelphiacitypennsylvania (accessed on 14 February 2024).
34. Shade, C.; Kremer, P. Predicting Land Use Changes in Philadelphia Following Green Infrastructure Policies. *Land* **2019**, *8*, 28. https://doi.org/10.3390/land8020028.
35. Locke, D.H.; Roman, L.A.; Henning, J.G.; Healy, M. Four decades of urban land cover change in Philadelphia. *Landsc. Urban Plan.* **2023**, *236*, 104764. https://doi.org/10.1016/j.landurbplan.2023.104764.
36. The Philadelphia Department of Public Health, Air Management Services. *Philadelphia's Air Quality Report*; City of Philadelphia: Philadelphia, PA, USA, 2022. Available online: https://www.phila.gov/media/20210316150355/PAQS_Report_Sept4-2020_final.pdf (accessed on 7 September 2023).
37. Logan, J.R.; Stults, B. *The Persistence of Segregation in the Metropolis: New Findings from the 2020 Census*; Brown Uiversity: Providence, RI, USA, 2021. Available online: https://s4.ad.brown.edu/Projects/Diversity (accessed on 16 June 2023).
38. American Lung Association. Pennsylvania: Philadelphia. 2022. Available online: https://www.lung.org/research/sota/city-rankings/states/pennsylvania/philadelphia (accessed on 23 April 2024).
39. Philadelphia Regional Center for Children's Environmental Health. *Asthma*; Philadelphia Regional Center for Children's Environmental Health: Philadelphia, PA, USA, 2023. Available online: https://prcceh.upenn.edu/focus-areas/asthma/ (accessed on 23 April 2024).
40. Philadelphia Department of Public Health. *Health of the City: Philadelphia's Community Health Assesment*; City of Philadelphia: Philadelphia, PA, USA, 2021.
41. Cummings, L.E.; Stewart, J.D.; Reist, R.; Shakya, K.M.; Kremer, P. Mobile Monitoring of Air Pollution Reveals Spatial and Temporal Variation in an Urban Landscape. *Front. Built Environ.* **2021**, *7*, 648620.
42. U.S. Census Bureau American Community Survey. 2020. Available online: https://data.census.gov/table/ACSDT5Y2020.B17010?q=poverty&g=050XX00US42101$1500000&tid=ACSDT5Y2020.B17010 (accessed on 23 April 2023).
43. U.S. Census Bureau Decennial Census. 2020. Available online: https://data.census.gov/table/DECENNIALPL2020.P1?g=050XX00US42101$1500000,42101&tid=DECENNIALPL2020.P1 (accessed on 23 April 2023).
44. United States Center for Disease Control. 500 Cities Project: 2016 to 2019. In *Places: Local Data for Better Health*; Centers for Disease Control and Prevention (CDC): Atlanta, GA, USA, 2020. Available online: https://www.cdc.gov/places/about/500-cities-2016-2019/index.html (accessed on 23 April 2024).
45. Cliff, A.D.; Ord, J.K. *Spatial Processes: Models & Applications*; Pion: London, UK, 1981; ISBN 978-0-85086-081-8.
46. Baker, R.S.; Brady, D.; Parolin, Z.; Williams, D.T. The Enduring Significance of Ethno-Racial Inequalities in Poverty in the U.S., 1993–2017. *Popul. Res. Policy Rev.* **2022**, *41*, 1049–1083. https://doi.org/10.1007/s11113-021-09679-y.
47. Hwang, J.; Ding, L. Unequal Displacement: Gentrification, Racial Stratification, and Residential Destinations in Philadelphia. *Am. J. Sociol.* **2020**, *126*, 354–406. https://doi.org/10.1086/711015.
48. Keet, C.A.; McCormack, M.C.; Pollack, C.E.; Peng, R.D.; McGowan, E.; Matsui, E.C. Neighborhood poverty, urban residence, race/ethnicity, and asthma: Rethinking the inner-city asthma epidemic. *J. Allergy Clin. Immunol.* **2015**, *135*, 655–662. https://doi.org/10.1016/j.jaci.2014.11.022.
49. Cliff, A.D.; Ord, J.K. Spatial Autoregression. *Economics* **1973**, *40*, 197–210.
50. Anselin, L. *Spatial Econometrics: Methods and Models*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 1988; Volume 4.
51. Guarnieri, M.; Balmes, J.R. Outdoor air pollution and asthma. *Lancet* **2014**, *383*, 1581–1592. https://doi.org/10.1016/S0140-6736(14)60617-6.

52. Tzivian, L. Outdoor Air Pollution and Asthma in Children. *J. Asthma* **2011**, *48*, 470–481. https://doi.org/10.3109/02770903.2011.570407.
53. Miranda, M.L.; Edwards, S.E.; Keating, M.H.; Paul, C.J. Making the Environmental Justice Grade: The Relative Burden of Air Pollution Exposure in the United States. *Int. J. Environ. Res. Public. Health* **2011**, *8*, 1755–1771. https://doi.org/10.3390/ijerph8061755.
54. Bell, M.L.; Ebisu, K. Environmental Inequality in Exposures to Airborne Particulate Matter Components in the United States. *Environ. Health Perspect.* **2012**, *120*, 1699–1704. https://doi.org/10.1289/ehp.1205201.
55. Collins, T.W.; Grineski, S.E.; Nadybal, S.M. A Comparative Approach for Environmental Justice Analysis: Explaining Divergent Societal Distributions of Particulate Matter and Ozone Pollution across U.S. Neighborhoods. *Ann. Am. Assoc. Geogr.* **2022**, *112*, 522–541. https://doi.org/10.1080/24694452.2021.1935690.
56. Bravo, M.A.; Anthopolos, R.; Bell, M.L.; Miranda, M.L. Racial isolation and exposure to airborne particulate matter and ozone in understudied US populations: Environmental justice applications of downscaled numerical model output. *Environ. Int.* **2016**, *92–93*, 247–255. https://doi.org/10.1016/j.envint.2016.04.008.
57. Cepeda, M.; Schoufour, J.; Freak-Poli, R.; Koolhaas, C.M.; Dhana, K.; Bramer, W.M.; Franco, O.H. Levels of ambient air pollution according to mode of transport: A systematic review. *Lancet Public Health* **2017**, *2*, e23–e34. https://doi.org/10.1016/S2468-2667(16)30021-4.
58. Krecl, P.; Johansson, C.; Targino, A.C.; Ström, J.; Burman, L. Trends in black carbon and size-resolved particle number concentrations and vehicle emission factors under real-world conditions. *Atmos. Environ.* **2017**, *165*, 155–168. https://doi.org/10.1016/j.atmosenv.2017.06.036.
59. Wu, B.; Wu, Z.; Yao, Z.; Shen, X.; Cao, X. Refined mass absorption cross-section of black carbon from typical non-road mobile machinery in China based on real-world measurements. *Sci. Total Environ.* **2024**, *908*, 168579. https://doi.org/10.1016/j.scitotenv.2023.168579.
60. Reyna-Bensusan, N.; Wilson, D.C.; Davy, P.M.; Fuller, G.W.; Fowler, G.D.; Smith, S.R. Experimental measurements of black carbon emission factors to estimate the global impact of uncontrolled burning of waste. *Atmos. Environ.* **2019**, *213*, 629–639. https://doi.org/10.1016/j.atmosenv.2019.06.047.
61. Ditas, J.; Ma, N.; Zhang, Y.; Assmann, D.; Neumaier, M.; Riede, H.; Karu, E.; Williams, J.; Scharffe, D.; Wang, Q.; et al. Strong impact of wildfires on the abundance and aging of black carbon in the lowermost stratosphere. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, E11595–E11603. https://doi.org/10.1073/pnas.1806868115.
62. Clean Air Council. Cleaner Commute. Available online: https://cleanair.org/transportation/cleaner-commute/ (accessed on 12 March 2024).
63. Ryder, O.S.; DeWinter, J.L.; Brown, S.G.; Hoffman, K.; Frey, B.; Mirzakhalili, A. Assessment of particulate toxic metals at an Environmental Justice community. *Atmos. Environ. X* **2020**, *6*, 100070. https://doi.org/10.1016/j.aeaoa.2020.100070.
64. Loh, P.; Sugerman-Brozan, J.; Wiggins, S.; Noiles, D.; Archibald, C. From asthma to AirBeat: Community-driven monitoring of fine particles and black carbon in Roxbury, Massachusetts. *Environ. Health Perspect.* **2002**, *110*, 297–301. https://doi.org/10.1289/ehp.02110s2297.
65. Krieger, N.; Waterman, P.D.; Gryparis, A.; Coull, B.A. Black carbon exposure more strongly associated with census tract poverty compared to household income among US black, white, and Latino working class adults in Boston, MA (2003–2010). *Environ. Pollut.* **2014**, *190*, 36–42. https://doi.org/10.1016/j.envpol.2014.03.015.
66. Krieger, N.; Waterman, P.D.; Gryparis, A.; Coull, B.A. Black carbon exposure, socioeconomic and racial/ethnic spatial polarization, and the Index of Concentration at the Extremes (ICE). *Health Place* **2015**, *34*, 215–228. https://doi.org/10.1016/j.healthplace.2015.05.008.
67. Northcross, A.L.; Hsieh, S.; Wilson, S.; Roper, E.; Dickerson, R.R.; Norouzi, P.; Morris, V. Monitoring Neighborhood Concentrations of PM2.5 and Black Carbon: When Using Citywide Averages Underestimates Impacts in a Community with Environmental Justice Issues. *Environ. Justice* **2020**, *13*, 27–35. https://doi.org/10.1089/env.2019.0026.
68. Suglia, S.F.; Gryparis, A.; Schwartz, J.; Wright, R.J. Association between Traffic-Related Black Carbon Exposure and Lung Function among Urban Women. *Environ. Health Perspect.* **2008**, *116*, 1333–1337. https://doi.org/10.1289/ehp.11223.
69. Rhynhart, R. *Mapping the Legacy of Structural Racism in Philadelphia*; Office of the Controller: Miami, FL, USA, 2020. Available online: https://controller.phila.gov/philadelphia-audits/mapping-the-legacy-of-structural-racism-in-philadelphia/ (accessed on 7 June 2023).
70. Jbaily, A.; Zhou, X.; Liu, J.; Lee, T.-H.; Kamareddine, L.; Verguet, S.; Dominici, F. Air pollution exposure disparities across US population and income groups. *Nature* **2022**, *601*, 228–233. https://doi.org/10.1038/s41586-021-04190-y.
71. Josey Kevin, P.; Delaney Scott, W.; Wu, X.; Nethery, R.C.; Priyanka, D.S.; Danielle, B. Dominici Francesca Air Pollution and Mortality at the Intersection of Race and Social Class. *N. Engl. J. Med.* **2023**, *388*, 1396–1404. https://doi.org/10.1056/NEJMsa2300523.
72. Maantay, J. Asthma and air pollution in the Bronx: Methodological and data considerations in using GIS for environmental justice and health research. *Health Place* **2007**, *13*, 32–56. https://doi.org/10.1016/j.healthplace.2005.09.009.
73. Łowicki, D. Landscape pattern as an indicator of urban air pollution of particulate matter in Poland. *Ecol. Indic.* **2019**, *97*, 17–24. https://doi.org/10.1016/j.ecolind.2018.09.050.

74. Weichenthal, S.; Pinault, L.; Christidis, T.; Burnett, R.T.; Brook, J.R.; Chu, Y.; Crouse, D.L.; Erickson, A.C.; Hystad, P.; Li, C.; et al. How low can you go? Air pollution affects mortality at very low levels. *Sci. Adv.* **2022**, *8*, eabo3381. https://doi.org/10.1126/sciadv.abo3381.
75. Hondula, D.M.; Davis, R.E.; Leisten, M.J.; Saha, M.V.; Veazey, L.M.; Wegner, C.R. Fine-scale spatial variability of heat-related mortality in Philadelphia County, USA, from 1983–2008: A case-series analysis. *Environ. Health* **2012**, *11*, 16. https://doi.org/10.1186/1476-069X-11-16.
76. Philadelphia Parks and Recreation. *Philly Tree Plan: Growing our Urban Forest*; City of Philadelphia: Philadelphia, PA, USA, 2023. Available online: https://www.phila.gov/media/20230223005617/Philly-Tree-Plan.pdf (accessed on 16 June 2023).
77. Walter, M.; Bagozzi, B.E.; Ajibade, I.; Mondal, P. Social media analysis reveals environmental injustices in Philadelphia urban parks. *Sci. Rep.* **2023**, *13*, 12571. https://doi.org/10.1038/s41598-023-39579-4.
78. VanderMeer, D. Diamond: A Struggle for Environmental Justice in Louisiana's Chemical Corridor. *Environ. Health Perspect.* **2005**, *113*, A68.
79. Tiwari, S.; Srivastava, A.K.; Bisht, D.S.; Parmita, P.; Srivastava, M.K.; Attri, S.D. Diurnal and seasonal variations of black carbon and PM2.5 over New Delhi, India: Influence of meteorology. *Atmos. Res.* **2013**, *125–126*, 50–62. https://doi.org/10.1016/j.atmosres.2013.01.011.
80. Kumar, P.; Morawska, L.; Martani, C.; Biskos, G.; Neophytou, M.; Di Sabatino, S.; Bell, M.; Norford, L.; Britter, R. The rise of low-cost sensing for managing air pollution in cities. *Environ. Int.* **2015**, *75*, 199–205. https://doi.org/10.1016/j.envint.2014.11.019.
81. EPA. AirNow. Available online: https://www.airnow.gov/ (accessed on 11 June 2024).