Mapping Social Vulnerability to Air Pollution in Philadelphia, PA

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Environmental stresses borne of population growth, consumerism and industrialization have subjected many populations worldwide to elevated air pollution. Philadelphia, a historically industrial city in Northeastern United States, is ranked in the top 25 cities in the country for harmful air pollutants (PM2.5, ozone). Philadelphia also experiences great financial stratification and environmental racism, which often unfairly asserts the pains of environmental pollution & associated health effects on socioeconomically disadvantaged communities. This study seeks to succinctly quantify which populations may be at risk for health effects associated with air pollution (specifically asthma, chronic obstructive pulmonary disease) through a suite of census-derived attributes. Using ArcMap Geographical Information System software (ESRI), attributes, categorized as promoting vulnerability or adaptability, are combined with air pollution data collected in summer 2019 to form a non-weighted 'Social Vulnerability Index' (SVI) at a census-tract level for Philadelphia. SVI demonstrated several clusters of neighborhoods with great disparities in socioeconomic factors. The census tracts with higher SVI tended to have higher levels of asthma and COPD (and vice versa). With improvements and acknowledgement of Philadelphia's uniqueness, SVI of this kind may be used to inform policymakers on city planning (e.g. placement of future highways, industrial centers, etc.) to alleviate compounded respiratory/ pulmonary-related stresses on disadvantaged communities. Future analysis including green space coverage, other forms of air pollution, and/or a quantification of social connectivity may help to improve further understanding of the intersection between socioeconomic factors, air pollution, and health in Philadelphia, PA.

Introduction

Ambient air pollution, often associated with globalization and related industrial activity, has become a well-known public health concern in many countries around the world (16, 20). Sustained poor air quality has been linked to a mosaic of health issues such as asthma, chronic obstructive pulmonary disease (COPD), infertility, birth defects, and lung cancers. Even short-term exposure to concentrated air pollutants can lead to emergency department visits, hospital admissions, and death (4, 25, 37).

$PM_{2.5}$, particulate matter (PM) with an aerodynamic diameter equal to or less than 2.5 µm, is especially damaging to human health (14). Ambient $PM_{2.5}$ has been identified as a leading international health risk factor, with 2.9 million attributable deaths worldwide in 2013 (5). $PM_{2.5}$ is dangerous due to its small diameter and potential to penetrate the lungs' gas-exchange region, invade the respiratory barrier, and enter the circulatory system. From the circulatory system, these particles can travel through the entire body and induce intracellular oxidative stress, mutagenicity/genotoxicity, and inflammatory response (14). There is even evidence of $PM_{2.5}$ damaging individuals' mental health. Through a large archival panel of 9,360 U.S. Cities, Lu et al. demonstrated a relationship between elevated $PM_{2.5}$ and criminal activity/ unethical behavior due to increasing anxiety (27). Szyszkowicz and Tremblay described an association between ambient air pollution and emergency department visits for depression among women (37). For these reasons, $PM_{2.5}$ has evolved as a common indicator of air pollution in the literature (24, 29) and will be used accordingly in this study.

Philadelphia, Pennsylvania has been ranked in the top 25 worst urban areas for air pollution in the United States for several years. According to the American Lung Association's 2019 report, the city is ranked 21st in the country for worst ozone pollution and 18th for worst annual $PM_{2.5}$ (34). Although the city is ranked in the top 25 for most particle pollution year-round, concentrations have improved since 2018. All rankings are based on the number of unhealthy days in 2015-2017. In 2018, PennEnvironment asserted that Philadelphia, despite its improving rankings, is not a healthy city in terms of air pollution (32). Furthermore, air pollution may not be evenly distributed amongst all populations, and vulnerable populations could be at greater risk for respiratory and pulmonary health effects.

Philadelphia is on an economic upswing, yet many of the city's residents continue to struggle financially. More than a quarter of the city's total population (~400,000 people) lives below the poverty line of about $19,700 per year for an adult with two children at home (19). Philadelphian's impoverished residents are twice as likely to describe their general health as poor or fair, with significantly higher levels of chronic illness (i.e. asthma, diabetes) asthma, diabetes) than other residents (19). Overall life expectancy can be as much as 20 years lower in poor ZIP codes than in wealthy ZIP codes (19). Could this varied life expectancy be connected to air pollution?

One approach for assessing the interaction between Philadelphia's $PM_{2.5}$, health issues, and socioeconomic disparities is the 'social vulnerability index' (SVI). SVI is a means for understanding the "potential for loss" in the case of disaster (9). This index can be conceptualized in two different ways: 1. vulnerability with the potential exposure to a physical hazard such as hurricanes or violent crime, and 2. vulnerability with exposure *as a given* such as air pollution and heat (45). Vulnerability to air pollution in Philadelphia can be taken "as a given" because it is assumed that areas in the urban core are constantly experiencing some level of impurity in the air. Communities experiencing this pollution are judged on their ability to withstand damaging effects; this is quantified as "resistance". In tandem, communities are also judged on their ability to recover quickly from damage; this is quantified as "resilience" (45).

Although these variables may change according to type and geographic location of assessment, commonly accepted factors for SVI are population density, gender, socioeconomic status, and/or public health conditions (13). These single variables are multidimensional, and may interact with a web of other explanatory factors; in other words, these single variables are highly correlated to many others (8). These variables are rooted in historical, cultural, social and economic processes that seem implicit in the way that certain communities react to exposure (8). We did not assign weight to SVI variables; several studies in social vulnerability (9, 11), climate-related coastal community hazards (45), and tornado disaster potential (35) did not weigh variables. These assessments are similar in structure to this study's methodology.

The following study aims to analyze the intersection of exposure, adaptability and vulnerability to air pollution in Philadelphia, Pennsylvania through a non-weighted, fine-spatial-scale social vulnerability index in tandem with an odds ratio describing asthma and chronic obstructive pulmonary disease (COPD). We hypothesize that the populations living in census tracts with high SVIs are more likely to experience elevated levels of asthma and COPD because these factors are shown to be correlated in previous literature (15, 18, 26).

Methods

Location

This analysis is prepared for the county of Philadelphia, Pennsylvania, located on the Eastern coast of the United States. The county has a population of about 1.6 million people over 134.10 square miles (30). Philadelphia is a historically industrial city, saddled between the Schuylkill and Delaware Rivers.

Selecting Relevant Indicators

Factors and descriptions used for computing vulnerability indicators, adaptability indicators, and health effects in previous social vulnerability studies are given in Table 1.

Table 1. Census Suite of indicators for social vulnerability index, categorized by factor. Each value is a percentage of total population. Indicators are color-coded: Vulnerability (yellow), Adaptability (blue), Health (grey). Includes data sources.

Factor	Indicator	Description	Utilized in previous studies	Data source
Age	Under 14 years old	Estimated percentage of population under 14 years old	(9, 16, 31)	(40)
	Over 65 years old	Estimated percentage of population over 65 years old	(9, 16, 27, 31)	
Gender	Female	Estimated percentage of female population	(9, 16, 27, 31)	(40)
Race	Non-White	Estimated percentage of Non-White population	(9, 10, 16)	(41)
Educational attainment	Little Education	Estimated percentage of population with less than a high school degree	(9, 16, 27, 31)	(42)
	Highly Educated	Estimated percentage of population with a Bachelor's degree or higher	(9, 16, 27, 31)	
Income	Poverty	Estimated percentage of population for whom poverty status is determined	(9, 11, 16, 31)	(43)
	Unemployed	Percentage of civilian labor force 16 years and older who identify as unemployed	(9, 11, 16, 27)	
	Wealthy	Percentage of population with income >$100,000 per year	(9, 11, 16)	(44)
Health Indicators	Crude Smoking	"Model-based estimate for crude prevalence of current smoking among adults aged equal or greater than 18 years, 2017"	(31, 39)	(6)
	Health insurance	"Model-based estimate for crude prevalence of current lack of health insurance among adults aged 18-64 years, 2017"	(31)	
	Checkup	"Model-based estimate for crude prevalence of visits to doctor for routine checkup within the past year among adults aged equal or greater than 18 years, 2017"	(22)	
Health Effects	Crude asthma prevalence	"Model-based estimate for crude prevalence of current asthma among adults aged equal or greater than 18 years, 2017"	(17, 23, 27, 38)	(1)
	Crude COPD	"Model-based estimate for crude prevalence of chronic obstructive pulmonary disease among adults aged equal or greater than years, 2017"	(3, 28, 36)	

Database Sources

We used the American Community Survey and the Centers for Disease Control 500 Cities Project for all socioeconomic and health data, respectively (Table 1). American Community Survey data is produced and disseminated by the Census Bureau's Population Estimates Program, which gives the official estimates of the population for the whole United States of America (40-44). The Center for Disease Control 500 Cities project provides city- and census tract-level estimates for many chronic disease risk factors, health outcomes, and preventive service use for 500 cities in the United States (1). Both of these datasets are publicly available, along with census-tract geographies. I used the Census Bureau's geography layer, and matched both of the datasets accordingly.

Point $PM_{2.5}$ measurements were made in summer 2019 (June 22 to July 29, 2019) by mobile air quality monitoring. A vehicle equipped with a rooftop aerosol monitor (pDR-1500, Thermo Scientific Inc.) was driven around Philadelphia for 12 days (~10 hours/day) with measurements taken every ~5 seconds. Overall, six total replicate measurements across Philadelphia county were taken and the spatial average of $PM_{2.5}$ for each census tract were used in this study.

SVI Score

In Excel, we computed the ratio for each indicator (Table 1) by dividing the original value by maximum value for all census tracts (Equation 1). This standardization process assures equal weighing for SVI values and that, in theory, one value is equally as influential as another in the total SVI.

$$Ratio\ Value = \frac{Original\ value}{Maximum\ original\ value\ for\ that\ attribute}$$

Equation 1. Calculating the 'Ratio Value'. This equation is applied to each attribute's column in Excel to assure equal weighting for census tract SVI values. Each value is calculated to two significant figures.

The final value for each census tract's values range from 0 to 1.00. Values closer to 1.00 indicate more vulnerability to the effects of air pollution. One exception is the enumeration of wealth—this is dichotomous; those with a yearly income of $100,000+ assigned a 1.00 and those with a yearly income of less than $100,000 assigned a 0.

$$Risk\ Index = Susceptibility + Exposure - Adaptability$$

Equation 2. Calculating the risk index for each census tract. This equation is applied to the Excel document with standardized variables.

Using Equation 2, we combined the standardized values to create a composite index score (or a 'risk index') for each census tract. This number is a quantification of each census tract's vulnerability to air pollution.

Odds Ratio

We generated a logistic regression using a *GLM* function fit with a binomial distribution in the *stats* package in *Rstudio* (3.6.0). *GLM* functions support non-normal distributions with non-constant variance. Crude COPD or asthma prevalence for each census tract were converted to dichotomous variables; the value "0" was given to census tracts whose asthma/COPD rates were less than citywide average, and the value "1" was given to census tracts whose rates were more than the citywide average. This was intended to estimate the probability (or "odds") that a census tract would have higher than average prevalence of each of these two diseases based on SVI value.

Geospatial Analysis

Maps were plotted in ESRI's ArcMap software by matching new composite index scores with the original geography layer (Figures 1-5). Choropleth groups are based on Jenks Natural Breaks Classification. This classification optimizes natural groups inherent in the data and is identified by software algorithm.

Results

Philadelphia, PA Composite SVI Values

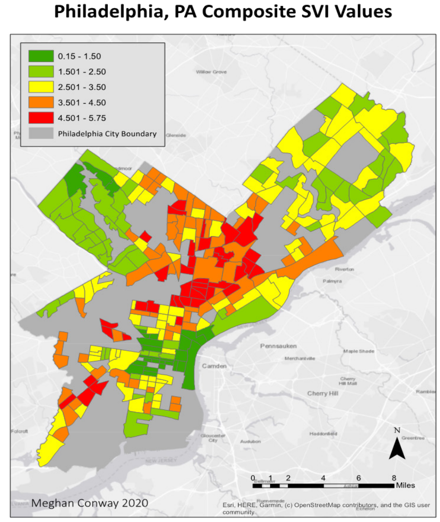

Figure 1. Census-tract-level, colored map of composite SVI values for Philadelphia county. Census tracks with the highest SVI values are red (4.501-5.75), and census tracks with the lowest SVI evaluations are green (0.15-1.50). Color scheme is generated with natural jenks.

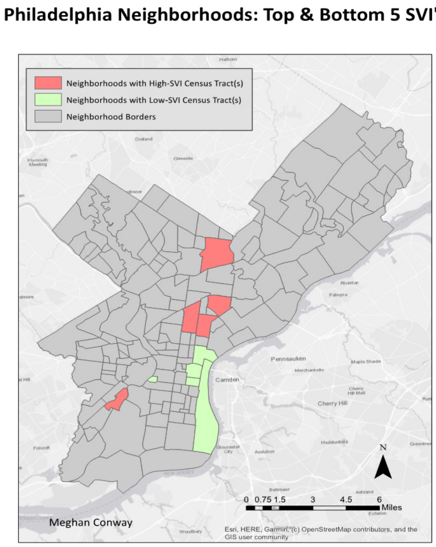

Figure 2. Neighborhood-level, colored map of highest and lowest values of SVI in Philadelphia county. Five highest census tracts are indicated by red and 5 lowest census tracts are indicated by green. Figure is created in ArcMap 10.8.

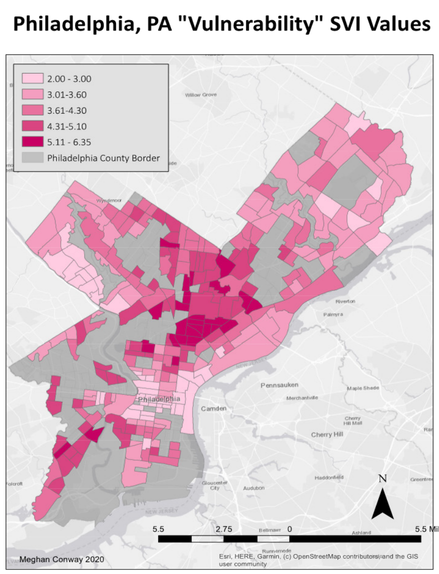

Figure 3. Census-tract-level, cho-rop-leth map of "Vulnerability" SVI Values for Philadelphia county. Ranges from 2.00 to 6.35. Darker colors indicate lessened community resilience to air pollution. Color scheme is generated by natural jenks. Figure is created in ArcMap 10.8.

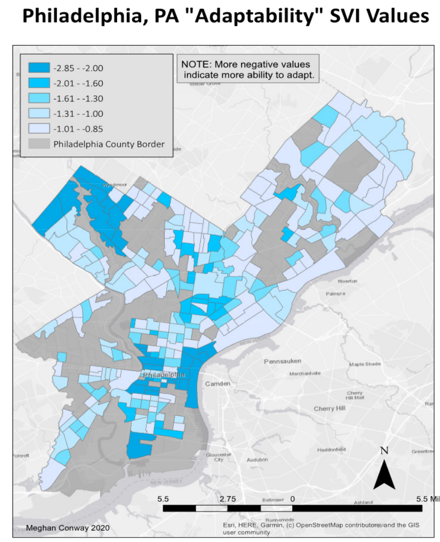

Figure 4. Census-tract-level choropleth map of "Adaptability" SVI Values for Philadelphia county. Ranges from -2.85 to -0.85. Darker colors indicate more community resilience to air pollution. Color scheme is generated by natural jenks. Figure is created in ArcMap 10.8.

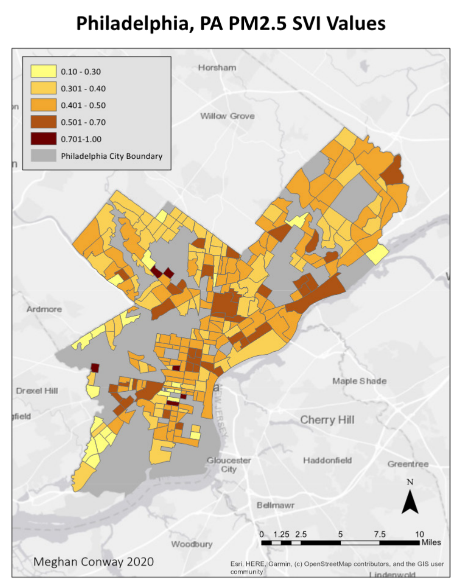

Figure 5. Census-tract-level, choropleth map of census-tract level pollution SVI values for the city of Philadelphia. Ranges from 0.10-1.00. Darker census tracts indicate higher average PM2.5 concentration. Color scheme is generated by natural jenks. Figure is created in ArcMap 10.8.

Overall, the SVI visualization (Figure 1) demonstrates a clear spatial pattern; North and Southwest Philadelphia clearly exhibit high vulnerability, low adaptability, and high $PM_{2.5}$, whereas Chestnut Hill and Center City demonstrate the opposite trends (Figures 3-5), suggesting that these three factors are interconnected in Philadelphia.

Average values for each attribute in Philadelphia are shown in Table 2. Those standardized original attributes whose averages are close to 1.00 have distributions that are more skewed towards the top quartile (i.e. female, checkup) and those attributes whose averages are close to 0.00 have distributions that are more skewed towards the bottom quartile (i.e. wealthy, little education). The attributes with the highest averages are the most consistent and normally distributed, whereas the lowest averages tend to indicate unpredictability. According to standard deviation and average values, the attribute with the most disparity amongst census tracts is wealth, but this may be attributed to its dichotomous nature. Vulnerability deviates significantly more from the mean than adaptability. This is likely a side effect of including more variables that contribute to vulnerability than adaptability.

Table 2. A summary of standardized attributes. Average and standard deviations for every standardized attribute in the suite of indicators as well as composite vulnerability, adaptability, and SVI values.

Standardized Attribute	Average	Standard Deviation
Checkup	0.86	0.06
Female	0.74	0.06
Smoking	0.52	0.14
Child	0.47	0.20
Pollution	0.43	0.09
Health insurance	0.37	0.18
Poverty	0.36	0.24
Highly Educated	0.32	0.25
Unemployment	0.32	0.17
Elderly	0.28	0.15
Little Education	0.28	0.19
Wealthy	0.12	0.33
Adaptability	**1.30**	**0.41**
Vulnerability	**3.87**	**0.91**
SVI	**3.00**	**1.05**

Census tracts in North and Southwest Philadelphia, which have been reported as historically disadvantaged (12, 19) display high SVI values (Figure 2). The neighborhoods with the highest SVI values ($\bar{x} = 10.54$, SD = 0.35) are: Bartram Village, Upper Kensington, West Kensington, Hartranft, and Olney. These neighborhoods are relatively clustered, indicating structural inequality.

In contrast, census tracts in Chestnut Hill and Center City have the lowest SVI values (Figure 2). The neighborhoods with the lowest SVI values ($\bar{x} = 0.34$, SD = 0.17) are in one area of the city along the Schuylkill River and the neighborhoods are: Society Hill, Old City, Riverfront, Northern Liberties, and Fitler Square. The area's SVI is significantly higher than the surrounding neighborhoods due to relatively elevated adaptability ($\bar{x} = 2.41$, SD = 0.21) (Figure 4), despite higher instances of $PM_{2.5}$ pollution (Figure 5). During air pollution data collection, these neighborhoods had numerous instances of construction and development that likely contributed to higher $PM_{2.5}$ values.

Upon viewing figures 3 and 4, a negative association between vulnerability and adaptability values for each census tracts seems to emerge. However, according to a linear regression of Adaptability Value vs. Vulnerability Value, this trend is not statistically significant (Figure 6). This may be due to the fact that many of the census tracts are low for both adaptability and vulnerability and are rather 'average' census tracts. This can be seen in figures 3 and 4; there is not much variation at all

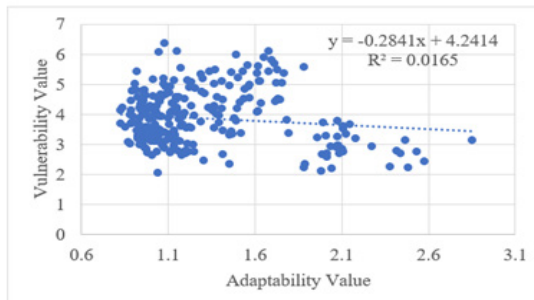

Figure 6. A linear regresssion of Adaptability Value vs. Vulnerability Value. Trend is overall negative with R^2 value of 0.0165 (not significant).

between the two maps in areas like Manayunk and Far Northeast Philadelphia.

The last step, the odds ratio, did not confirm a significant relationship between elevated levels of COPD/asthma and SVI (Table 3). Although statistically insignificant, there is a positive relationship between high SVI and higher than average asthma prevalence according to the odds ratio (OR) values (Table 3).

Table 3. Odds Ratio values. Results of logistic regression using a GLM function fit with a binomial distribution in the *stats* package in *Rstudio* (3.6.0).

Variable	City Prevalence	Odds Ratio (OR)	P-value
Asthma	11.5%	1.19323	0.1455
COPD	7.2%	0.96360	0.751

Discussion

Geospatial results introduce several interesting socioeconomic trends in Philadelphia, PA. The results of the odds ratio do not confirm a relationship between

SVI and increased asthma/ COPD prevalence.

There are clear historical differences between the five census tracts which are highest in SVI and lowest in SVI. As iterated in the results section, the five neighborhoods with the highest social vulnerability are Bartram Village, Upper Kensington, West Kensington, Hartranft, Olney. These neighborhoods are generally examples of areas with historically structural poverty. Several of the pictures in "Philadelphia's Poor: Experiences From Below the Poverty Line" report by the PEW Charitable Trust depict life in Kensington with many residents struggling with unemployment, poverty, drugs and crime (19, 33). In the 1960s and 1970s, pockets of poverty were limited to a few neighborhoods subjected to rapid deindustrialization, but in recent years (up to 2016), the geographic distribution of poverty has increased steadily (19). This increasing distribution of poverty, coupled with evidence of historically structural poverty, calls for a revamp of the city's resource allocation. In contrast, the five neighborhoods with the lowest social vulnerability are generally a collection of the oldest neighborhoods in the city, founded by the English Quakers during the seventeenth century settlement of Philadelphia. This area, especially Society Hill, was historically poor, but has recently been redeveloped, gentrified, and occupied by historical preservationists (2). These historical differences may feed and reinforce current socioeconomic, environmental pollution and health conditions within their populations.

The odds ratio prescribed to connect the SVI to asthma and COPD did not produce statistically significant results. This does not disprove the relationship between these health outcomes and air pollution, but rather requires us to delve into the methodology behind quantifying this connection. One issue may be the strong correlation between some attributes used to create the SVI, known as 'ecological correlation' (7). This is an issue of aggregation bias, which may be expected when concatenating large datasets. However, this bias may be partially alleviated by removing highly correlated attributes. One such attribute is poverty, which has a strong linear relationship with both low education (Figure 7) ($R^2 = 0.5308$, $p < 0.001$) and access to healthcare (Figure 8) ($R^2 = 0.6194$, $p < 0.001$). For comparison, linear regressions of noncorrelated variables appear similar to figure 9 ($R^2 = 0.0827$, $p < 0.001$). Issues associated with impoverishment may have influenced education levels and access to healthcare. Thus, including low education and access to healthcare in the overall SVI in addition to poverty creates a statistical atmosphere which over-emphasizes poverty's impact. A careful development of a new social vulnerability attribute suite may also be compared with other social vulnerability indices from other cities, thus giving insight into the unique impact of air quality on Philadelphians.

The way that we account for air pollution may also play a part in the real-life application of SVI. Often times, there is great uncertainty in the effect that air pollutants (especially $PM_{2.5}$) will have on citizens' health. One study, based in Boston, MA, discusses the variation in the relationship between ambient $PM_{2.5}$ and hospital admissions in cities across the United States (24).

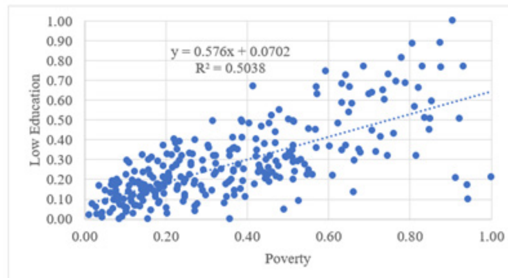

Figure 7. A linear regression of poverty and low education in Excel. Trend is positive. $R^2 = 0.5038$, p-value <0.001.

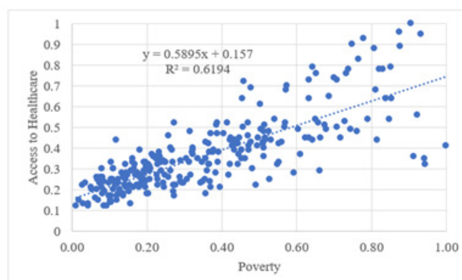

Figure 8. A linear regression of poverty and low education in Excel. Trend is positive. $R^2 = 0.6194$, p-value <0.001.

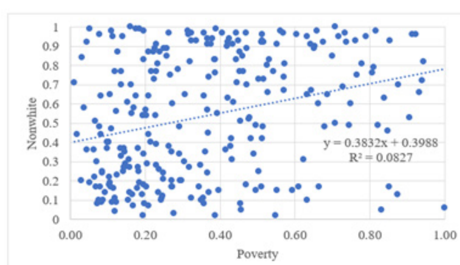

Figure 9. A linear regression of poverty and low education in Excel. Trend is positive. $R^2 = 0.0827$, p-value <0.001.

Differences in particle composition may lead to varied toxicity and varied health effects. Thus, it is difficult to relate $PM_{2.5}$ in Philadelphia to only two specific health effects; future study should choose a larger portion of respiratory and pulmonary diseases as to account for possible varied health effects.

There are three succinct, final future directions which may aid in giving a more holistic picture of each community's vulnerability to the health effects of air pollution. First, it would be helpful to include some aspect of the built environment, such as green space coverage, impervious surfaces, or some quantification of area assigned to parks and recreation. Often, the influence of green space on microclimate can offset air pollution (9). Additionally, assessing the effects of other forms of air pollution (such as varied sizes and components of particulate matter and trace gases) may be useful to tease out a an alternate 'indicator pollutant' for Philadelphia, which may differ from studies in other cities. Lastly, some quantification of social connectivity, such as social capital, may be useful in assessing a community's ability to adapt to environmental pollution. Social capital is "a term that is used to describe a related group of community characteristics including social trust, norms of reciprocity and cooperation and civic engagement" (21). The strength of a community may not only be assessed in its socioeconomic characteristics and built environment, but also social resilience.

Overall, Philadelphia is a unique city and must be treated as such when choosing variables and how they may affect a given population. After making the described improvements, this same methodology could be used to inform policymakers on the placement of polluting sources, risk allocation, and risk management to protect stressed communities from compounded respiratory and pulmonary issues in the short- and long-term (16, 35).

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