Exposure to Respiratory Hazards and Educational Performance in the Riverside Unified School District, California: A Geospatial Analysis

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Introduction

Situated in the Inland Empire region of California, Riverside County has some of the highest rates of particulate matter pollution throughout the state. With the American Lung Association grading Riverside County air quality an "F," coupled with its ranking of second worst air pollution in the state, it is clear that Riverside County residents are constantly exposed to high levels of aerosol pollutants. [1, 2] Air pollution, particularly exposure to particulate matter and respiratory hazards, has adverse impacts on human health. Air pollution exposure has been attributed to high rates of pediatric and adult asthma, cardiovascular disease, and chronic obstructive pulmonary disease (COPD). [1] Regional agencies such as the South Coast Air Quality Management District have emerged in an effort to support communities impacted by poor air quality, especially since the topography of Southern California makes Riverside County more prone to negative health impacts due to smog collecting in the region, being blown in from Los Angeles. [3]

Though the effects of particulate matter exposure on health outcomes are well researched and documented, there is limited academic research on the impacts of respiratory hazard exposure and educational outcomes. Previous works have sought to find associations between air toxics exposure and decreased academic performance, primarily through a public health and environmental science lens. In a study of school children in China, researchers found a significant association between air pollution, particularly levels of NO_2, and poorer results on neurobehavioral tests designed to measure the children's sensory, motor, and psychomotor functions. [4] Furthermore, existing literature has suggested that minority children, notably Hispanic and African-American children, are exposed to higher levels of air pollution in comparison to white children. [5, 6, 7] African-American children are exposed to air pollution at disproportionate rates, even higher than Hispanic children. [5] Low income communities are also exposed to air pollution at higher rates. Academic studies have found that low-income California communities were exposed to PM 2.5 almost 10% higher than the state average of exposure. [7]

Pollutants that are suspected or known toxicants have been noted to have an effect on school performance surpassing socioeconomic (SES) variables, and that school performance and toxicant exposure is statistically significant. [8] Studies show that areas with higher levels of residential air toxics are associated with lower grade point averages, and that there is a correlation between respiratory risk and lower economic performance even after controlling for SES. [8, 9] These studies, however, fail to assess the correlation between air toxin exposure and educational outcomes from a geospatial perspective. Understanding and mapping the health geography of environmental hazards and educational outcomes, as well as assessing the spatial relationship between the two, are practical and may be used by policymakers to influence change in environmental policy if academic outcomes are low in regions with high levels of respiratory hazards.

This work seeks to assess the impacts of respiratory toxins on educational outcomes using spatial methods, which have yet to be done in an empirically rigorous manner. This is done by using Riverside Unified School District (RUSD) as a case study to understand whether air toxin exposure and academic performance are correlated. Through this study, we are able to assess the correlation using pure spatial sciences and contribute to the limited body of knowledge studying environmental toxin exposure and academic outcomes.

Methods

This work draws from open data, software, and open science; this is discussed in more detail throughout this section. This study relies on spatial data science and novel econometric methods to assess the relationship between respiratory toxin exposure and academic outcomes in RUSD.

Data sources

Data sources used in this study are publicly available and free of cost. The 2020 Environmental Justice Screening and Mapping Tool (EJSCREEN) data provided by the U.S. Environmental Protection Agency was quintessential in assessing exposure to respiratory toxins. The EJSCREEN tool makes data on environmental and demographic data easily accessible to the public and also integrates EPA's own unique environmental indexes. [10] To assess respiratory hazards, this study used the National Scale Air Toxics Respiratory Hazard Index, paired with the EPA's Environmental Justice (EJ) measure. This measure seeks to incorporate both environmental exposures with demographic factors such as race, income, and disability; the study used the EJ index for air toxics respiratory hazard index. Higher EJ index values for air toxics respiratory hazards imply that more low-income minorities are being impacted by respiratory air toxics. [10] The EJSCREEN tool also included separate demographic information such as race/ethnicity, income, etc. which were used later in the study.

To map this data onto census block groups within the boundaries of RUSD, we utilized two significant data sets. Data from the 2018 American Community Survey (ACS) was used to join EJSCREEN data to census block group data, so we would be able to view the EJ index for air toxics respiratory hazards per block group in the Riverside School District. We also used the

U.S. Department of Education's National Center for Education Statistics (NCES) data, which includes information surrounding school district boundaries and locations [11]. Using the 2018-2019 NCES dataset, we were able to isolate the RUSD boundaries and map them out. This dataset, however, is not inclusive of school outcomes or academic performance. Therefore, this study also utilized data sourced from the Stanford Education Data Archive (SEDA), curated by the Educational Opportunity Project at Stanford University. This data includes information surrounding K-12 academic achievement such as standardized test scores, which we are particularly interested in assessing [12]. In this study, we utilized average standardized test score values among 3rd to 8th graders in math and reading language arts from the 2008-09 through 2017-18 academic school years.

Combining environmental and educational datasets

As mentioned previously, we were tasked with the responsibility of joining the EJSCREEN data to the ACS block group data to map the EJ index for air toxics respiratory hazard index; this way, we would be able to look at the EJSCREEN data per census block group. These two data sets were merged and then adjusted to only display data within Riverside County. From there, we overlaid the NCES school district boundaries from RUSD over this existing data layer to display EJSCREEN data per block group within RUSD boundaries. We were able to then generate a basic visualization of the EJ index for air toxics respiratory hazard index per block group within RUSD, as seen in Fig. 1. This visualization was done via the creation of a choropleth map; dark blue block groups represent higher values for the air toxics respiratory hazard index, whereas lighter colored block groups represent lower values. Therefore, darker census block groups display regions where higher numbers of low-income minority groups within RUSD are being exposed to air toxins and respiratory hazards.

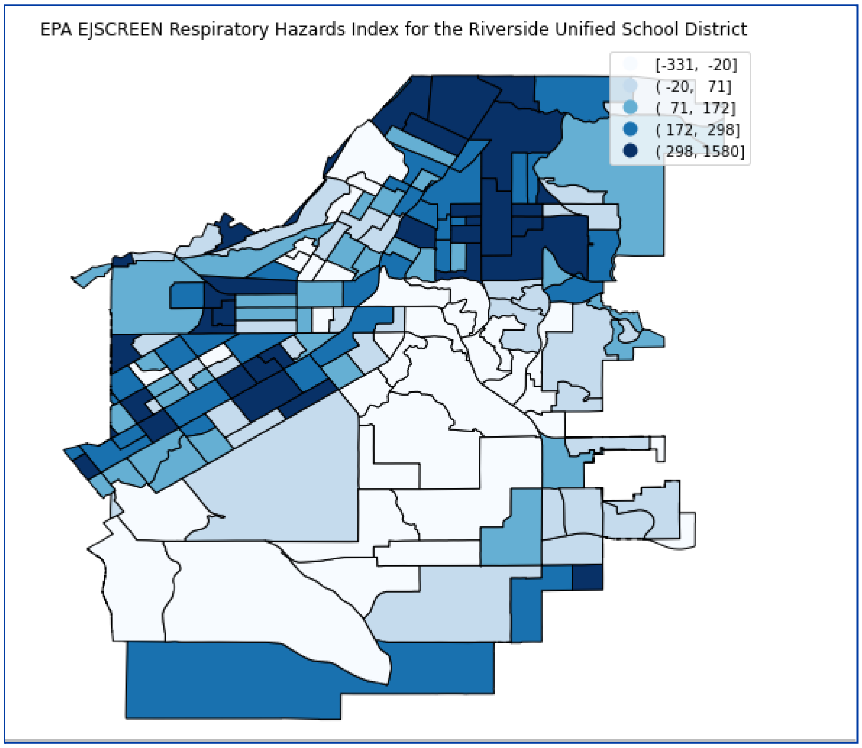
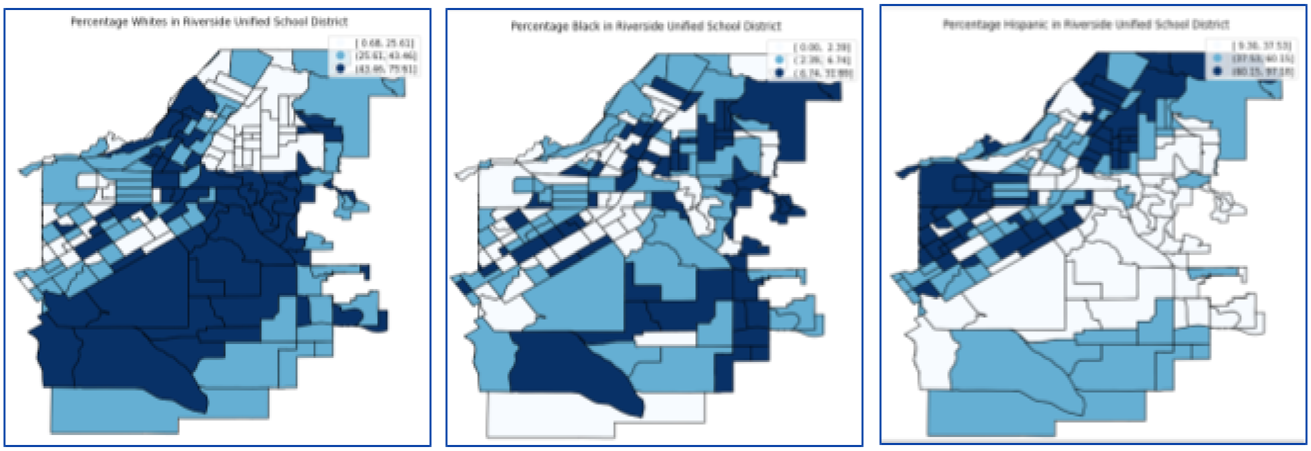


Fig. 1. EJ index for air toxics respiratory hazard index per block group within RUSD

Using the EJSCREEN data, we were also able to create choropleth maps of the racial/ethnic composition of RUSD. Fig. 2 highlights the three choropleth maps generated using EJSCREEN data, which display the racial/ethnic distribution of white, Black, and Hispanic groups within census tracts in RUSD.



a.Percent White
Highest Quantile:43- 75

b.Percent Black
Highest Quantile:6- 31

c.Percent Hispanic
Highest Quantile : 60- 97

Fig 2. Racial/ethnic distribution of individuals within block groups in RUSD

From there, we combined the SEDA data set to find point geometry for each school. Our resulting sample for RUSD has a total of 39 observations for the average test scores administered from the 3rd grade to the 8th grade in math and reading language arts. The educational outcomes were visualized and mapped on the block group boundaries. Fig. 3. displays the plotted educational outcomes within RUSD schools; one can infer that educational outcomes throughout RUSD very heavily, with values being primarily low across the board.

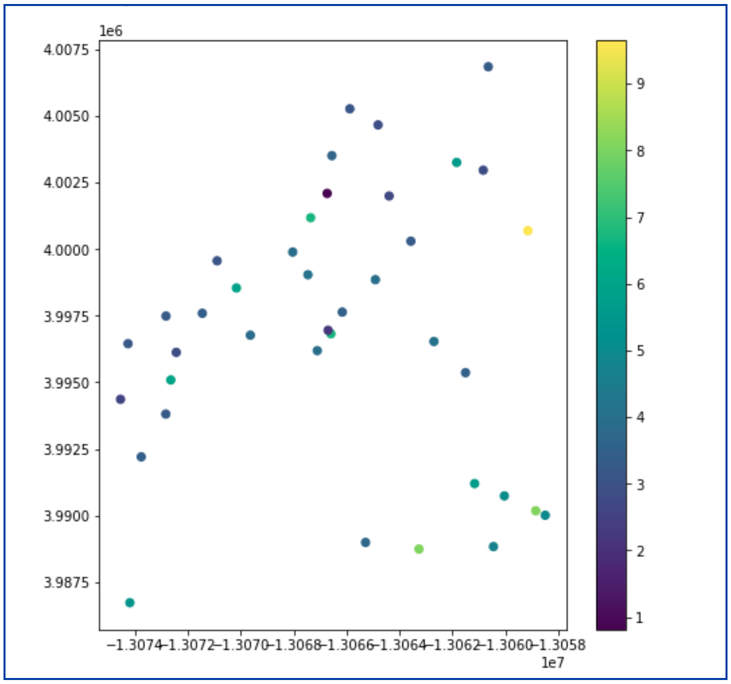


Fig. 3. Educational outcomes for RUSD schools (plot)

We were able to plot these points onto the RUSD boundaries by joining the data to the ACS block groups within RUSD boundaries, which is displayed in Fig. 4. This was done to provide us with a joint visualization of the school locations, their performance, and the spatial location of which they reside inside of RUSD.

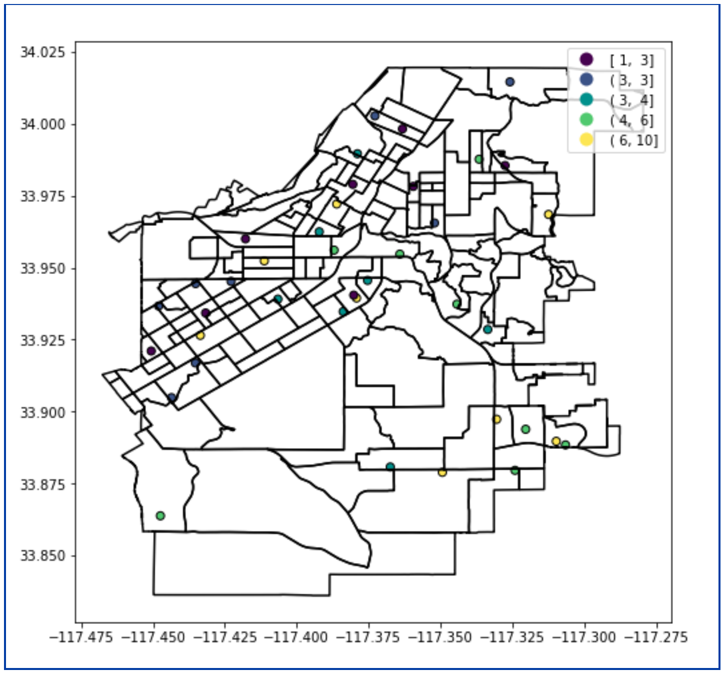
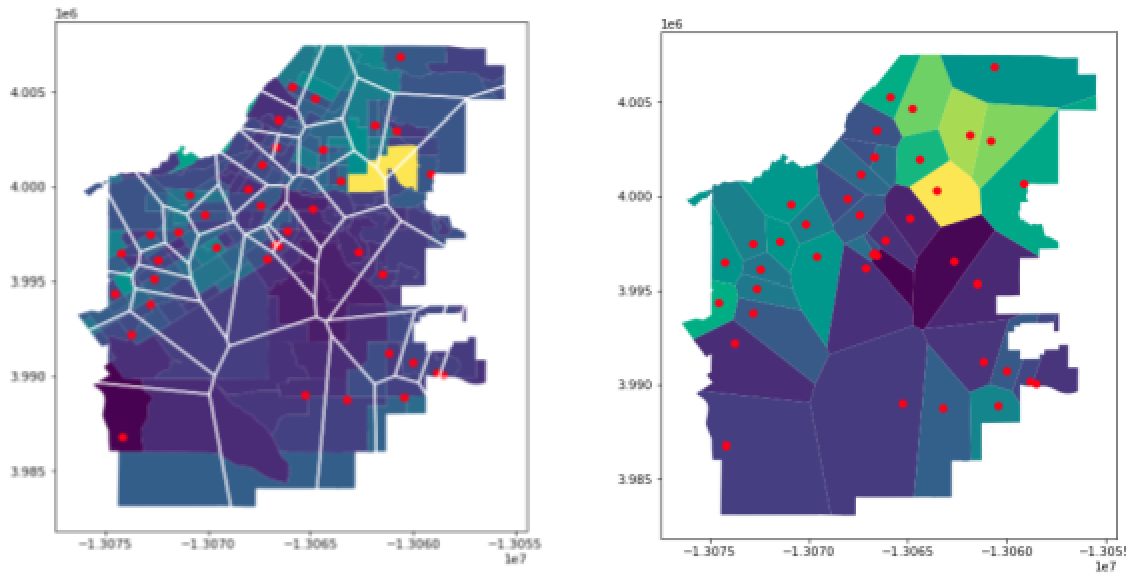


Fig. 4. Educational outcomes and locations for RUSD schools

Spatial analysis

Once variables and data were staged for mapping, the spatial analysis implemented was the Voronoi method. Fig. 5 displays the differences between a one-to-one spatial join approach (Map A), as well as the areal interpolation and Voronoi analysis (Map B). Utilizing the Voronoi method to create a simple map visualization and assess data is beneficial, as it is consistent in mapping out the centroids (represented by a point) within polygons, based on the location of other nearby polygons. In other words, each polygon contains exactly one generating point and every point in a given polygon is closer to its generating point than others. [11] Within the geospatial analysis, this technique is used for illustrating distance within a polygon to its centroid and access. For the purposes of our project, we were able to generate polygons that demonstrated student distances to schools, which schools they were assigned to and the environmental respiratory hazard index that accompanied each polygon.



Map A - 1 to 1 Spatial Join **Map B- Areal Interpolation**

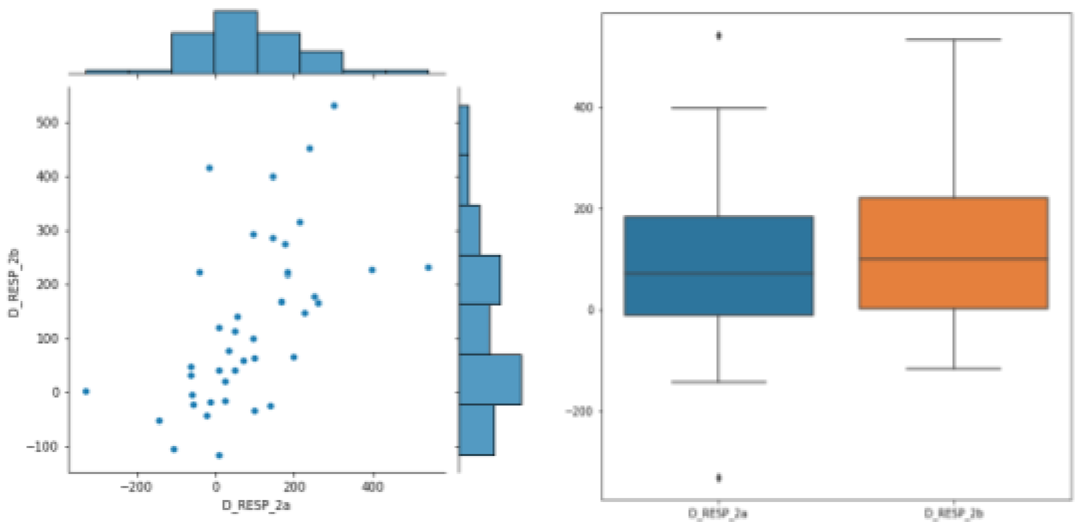
Fig. 5. Maps for Voronoi analysis

Map A demonstrates a one- to-one spatial join, and within each white catchment zone (white polygons), the red dot represents the school location within RUSD. The one-to-one spatial joins took the value for the environmental zone that contains the school in a one-to-one relationship; in a sense, it could be compared to a table join. The Voronoi method, on the other hand, constructs a value that highlights the environmental quality in the neighborhoods closest to the school, in a one-to-many relationships. This, therefore, considers more factors than the one-to-one spatial join, which was why we focused on it more heavily than the other method. Finally, we superimposed tract and block group respiratory hazard data in each boundary. Each census block group then has a score and color scheme accompanied. The project then implemented an areal interpolation algorithm in that it weights each absolute value within the tract and block group polygons and overlaps it within each appropriate white catchment zone. In other words, areal interpolation is the process of making an estimate. Therefore, each white catchment post areal interpolation has a new score and color scheme.

Darker blue/purple areas represent a better air hazard index, while lighter green and yellow represent hazardous air index scores. To compare Fig. 5 with Fig. 2 clusters of percent white are clustered in the southern part of the Riverside Unified School District and are seen with a better air hazard index. In contrast, percent Hispanic is clustered in the northern areas of Riverside Unified School District and has a worse air hazard index. Percent Black is randomly distributed among Riverside Unified School District and represents an in-between hazard index score.

Results and discussion

We estimated two separate indices for Environmental Justice air toxics respiratory hazard using the two approaches mentioned earlier. Fig. 6 presents a comparison of the two indices. The scatter plot shows that EJ index A based on one-to-one spatial join is highly correlated with EJ index B from areal interpolation. This association is also visible by comparing the variations in the distributions as shown in the box plot (Fig. 6). We estimated two separate indices for Environmental Justice air toxics respiratory hazard using the two approaches mentioned earlier. Fig. 6 presents a comparison of the two indices. The scatter plot shows that EJ index A based on one-to-one spatial join is highly correlated with EJ index B from areal interpolation. This association is also visible by comparing the variations in the distributions as shown in the box plot (Fig. 6). The box plot for EJ index A (shown in blue) has outliers whereas the areal interpolation method helps to factor those into account as depicted by the distribution of EJ index B, which leads to different results. To understand how the Environmental Justice air toxics respiratory hazard index is related to educational outcome (test scores from SEDA) we plotted two separate scatter plots for each of the estimated indexes.



Scatter Plot **Box Plot**

Fig. 6. Comparison of the two EJ indices (A and B)

We estimated two separate indices for Environmental Justice air toxics respiratory hazard using the two approaches mentioned earlier. Fig. 6 presents a comparison of the two indices. The scatter plot shows that EJ index A based on one-to-one spatial join is highly correlated with EJ index B from areal interpolation. This association is also visible by comparing the variations in the distributions as shown in the box plot (Fig. 6). The box plot for EJ index A (shown in blue) has outliers whereas the areal interpolation method helps to factor those into account as depicted by the distribution of EJ index B, which leads to different results. To understand how the Environmental Justice air toxics respiratory hazard index is related to educational outcome (test scores from SEDA) we plotted two separate scatter plots for each of the estimated indexes.

Fig. 7 shows the results of the two indices. The plot on the left shows the relationship between EJ index A and educational outcomes, looking at the plot we find no clear patterns of correlation between the two variables. Similarly, the plot on the right shows results from the EJ index B on the horizontal axis and educational outcomes on the vertical axis. Here we can see the spread of the distribution has changed.

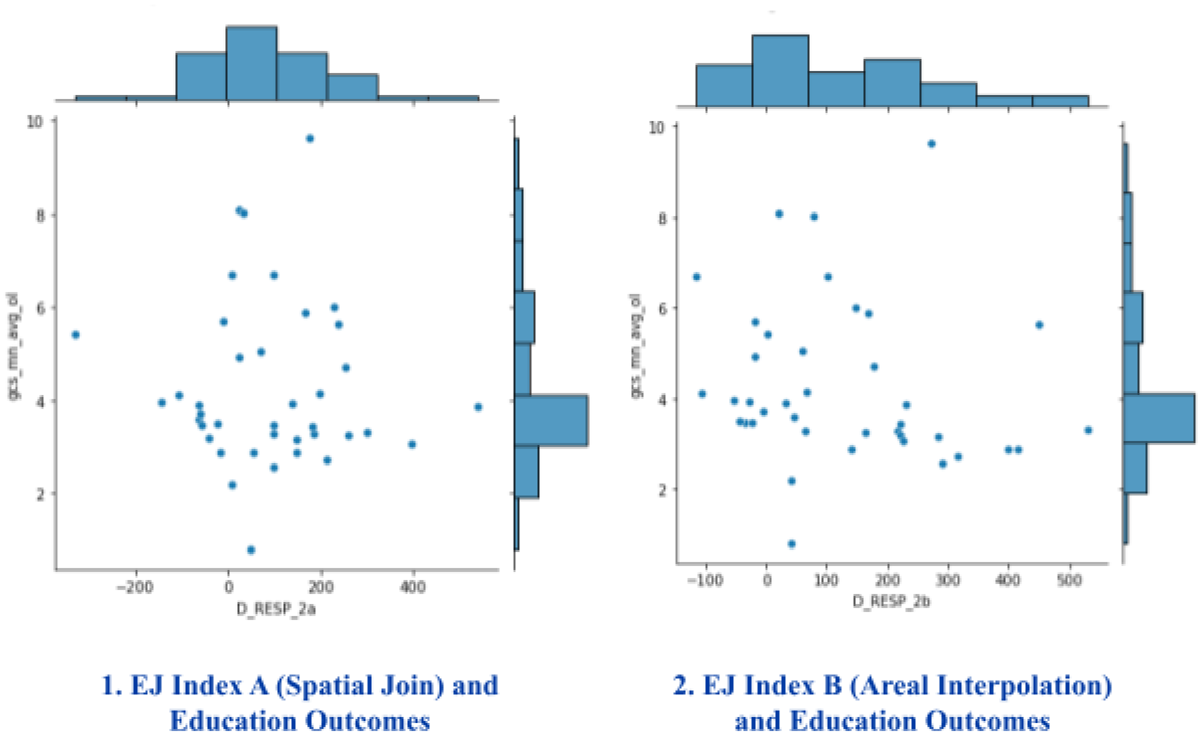


Fig. 7. Scatter plot for EJ air respiratory hazards indices and educational outcomes

Between the EJ index 2 and educational outcomes, we find some evidence of a negative correlation. This is consistent with past literature and our hypothesis. Educational outcomes such as test scores decline when students are exposed to a higher burden of respiratory hazards. One possible explanation is that the location of the schools determines access. Students usually attend school in their closest neighborhood. Whenever the schools are situated in areas with a higher pollution burden the exposure of students to undesirable toxins also increases. Higher exposure translates into adverse health risks and a decline in the schooling performance of the students.

In order to better understand the association between respiratory hazard exposure and educational outcomes, we plotted the best fitting lines through each of the points on the scatter plot. This line is similar to an ordinary least squares regression that minimizes the vertical distance from the data points on the scatter plot. Fig. 8 shows the line plots through the scatter plots for both EJ index A and EJ index B on the same graph.

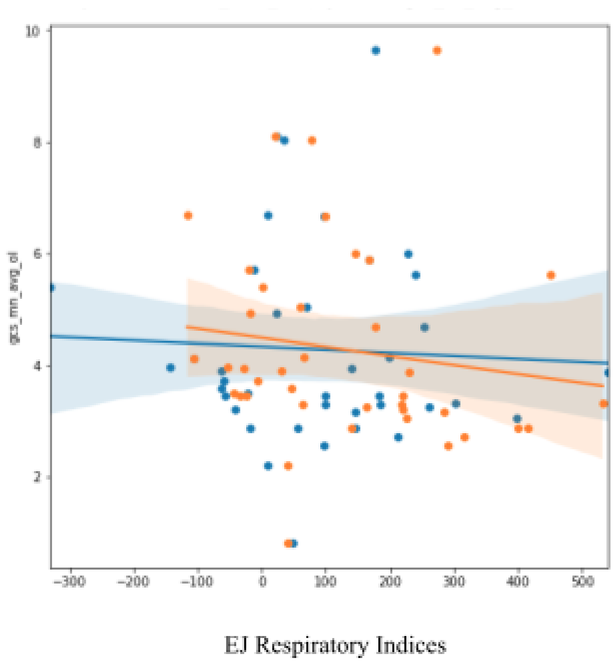


Fig. 8. Comparison of spatial join and areal interpolation

As displayed in Fig. 8, there is a slight negative correlation between academic outcomes and exposure to respiratory hazards. The blue line, which represents the spatial join values, saw a much smaller decrease in scores compared to the orange line, which represents the areal interpolation values. This may be attributed to higher levels of variability among that data due to generated values being estimates. However, considering the catchment zone there is variability in our study because the block groups within the EJSCREEN have large numbers consisting of mainly low-income and/or minority residents with a "higher environmental indicator value" [10].

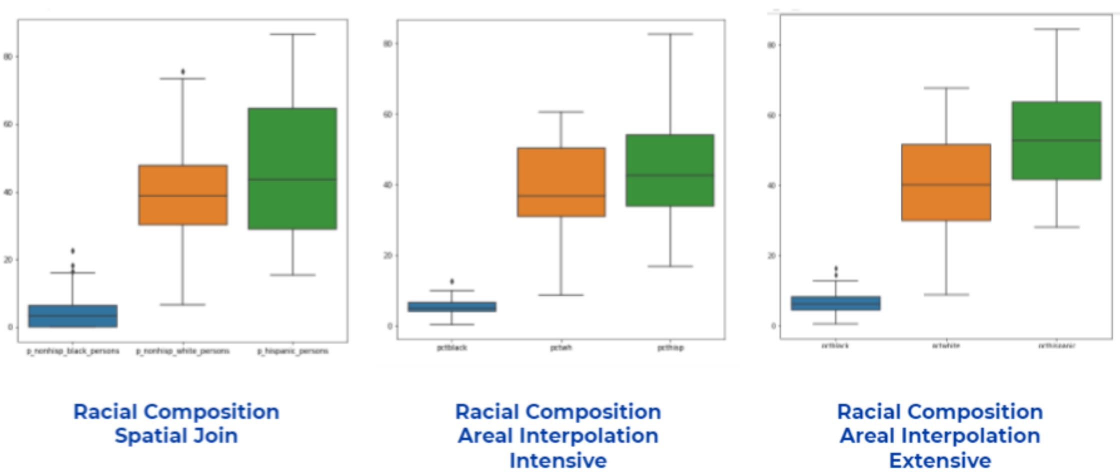


Fig 9. Comparison of racial composition using Voronoi

After we worked on the respiratory indexes and educational outcomes, we also looked into the racial composition of RUSD. As mentioned in the literature, racial inequality is part of the environmental injustice so we looked into minority populations as well. Therefore, to test for differences in educational outcomes, we selected three racial groups: White, Black, and Hispanic. Then, we conducted the Voronoi method using percentages provided by the ACS census tracts dataset. The first figure from Fig 9. shows the one-to-one spatial join relationship using percentages. Then for the second figure, we re-estimated the percentages using areal interpolation with the intensive values which showcase how the values of each racial group are slightly different from the one-to-one association from the first figure. While the third figure shows areal interpolation with the extensive values, total count of the racial groups, which was the third approach we utilized for our re-estimation.

Therefore, our study shows that there is an association between exposure to respiratory hazards and educational outcomes. Specifically, it shows that there is a decline in educational performance among primarily low-income minority students exposed to respiratory toxins and hazards. Hispanic students within RUSD are particularly impacted by this, as we plotted the different racial groups and their educational outcomes to better understand educational performance by race.

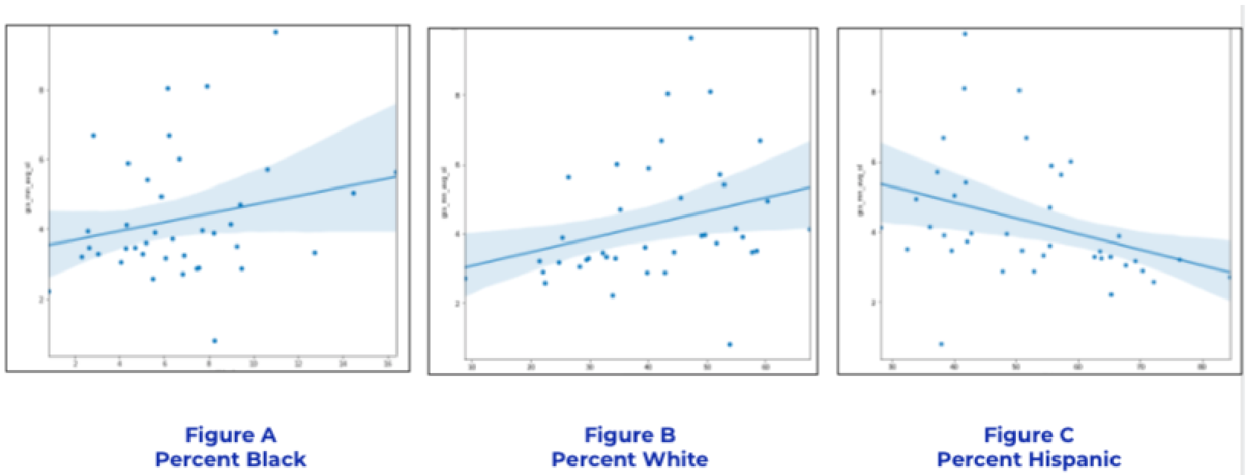


Fig 10. Educational outcomes by race/population in RUSD

Fig. 10 displays the results, and it is observed that Hispanic students see a significant decline in academic performance as their population increases. Black and white students, particularly Black students, are a much smaller population compared to Hispanic students. Even if Fig. 10 shows an increase in academic performance among those groups in RUSD, that is more true for white students since their population is larger than the Black population. Therefore, we can conclude that Hispanic students are particularly impacted by respiratory hazard exposure as they see a larger academic decline and are the largest population within RUSD. Through this association and correlation are indicative of these trends, it is also important to note that correlation does not mean causation; further research must be done to find a stronger association.

Data and analytical limitations

The EJSCREEN dataset from the EPA has its limitations. For example, the dataset has some "uncertain estimates"; specifically, in small block groups [10]. Although it has this limitation the dataset is recommended to use for summarizing the data in big areas, so that it may cover multiple block groups. The second limitation is that the dataset does not provide all possible environmental impacts and demographics. The reason why that is the case is that there are many components within environmental factors that have not been assessed and included in national databases such as the quality of drinking water or indoor air quality. The third limitation is that the income percentages are estimates, they may be over or underestimates because the data does not count for all households from the U.S. Census. Furthermore, the variables calculated are for “each block group” except specific environmental indicators “for air quality” such as the air quality of particle matter or ozone. [10] These air quality indicators were assessed for each Census tract or block group. Lastly, when using EJSCREEN is it important to consider that the EJSCREEN dataset ultimately represents a proxy for assessing the possible health impacts in the United States.

Additionally, SEDA data may not be an accurate indicator of academic performance. Though standardized test scores are a traditional indicator of academic performance, factors such as SES, academic capacity, disability, and test-taking abilities may impact score outcomes. School district academic ranking, academic preparation, and resources to support student success may also influence academic performance. Perhaps regions with higher exposure to environmental hazards such as respiratory hazards have schools that are significantly underfunded, understaffed, or with limited resources to train students for standardized exams. However, both the EJSCREEN and SEDA data allow us to begin assessing and understanding if there is a relationship between environmental exposure and academic outcomes, with the potential to be built upon.

Future research and policy recommendations

Researchers and policymakers should consider doing in-depth studies, addressing whether or not existing environmental policies(such as the famous Cap and Trade Program) lead to better environmental outcomes. In addition, researchers should consider if the "better" environmental outcomes lead to better health outcomes, especially in students. Ultimately, the nature of our research represents a proxy model to demonstrate whether a school's test performance is associated with air toxic pollution exposure based on geospatial location. Furthermore, our second policy recommendation is for researchers to use our documentation and methodologies to not only replicate our study but expand it as well by analyzing other counties and schools. A benefit for expanding our study is that researchers can estimate the geospatial visualization of air toxic pollution in other regions. Through our research, we are laying the foundation for other researchers that are interested in environmental issues.

After showcasing the results and discussing the policy recommendations, it is important to reiterate the importance of this study because the negative issues surrounding environmental air hazards and the impact on school performance is a highly neglected and under-researched exploration. Also, it is imperative that our study can be utilized as a way to further expand future research on this subject. Future work should assess how accurate the spatial analysis method is in finding correlations between spatial data and educational outcomes, and more rigorous statistical methods should be used to better understand the association.

Conclusion

The relationship between environmental exposure on student academic performance is an emerging research study that remains incomplete. Our model can serve as a template for future research projects that highlights the importance of implementing clean environmental policy standards and their potential impacts on student achievement. There are several caveats to the association between environmental exposure and academic achievement. This too includes our research study where our topic is one function among many that can impact a student's ability to do well in their school work. In other words, other functions such as parental involvement, quality of the neighborhood, academic support, all serve other variables that can also show an association to student achievement. Showcasing our results and investing research resources can contribute to the breadth of knowledge that assesses how air toxins impact student academic achievement.

Data availability

The data underlying the results presented in the study are openly available in GitHub at https://github.com/preetijuturu/p280s21project3. In addition, the documentation of how our project was implemented can be located via https://github.com/preetijuturu/p280s21project3/blob/main/Documentation%20Overview.md.

References

1. American Lung Association. State of the Air: Riverside [Internet]. American Lung Association. Available from: https://www.lung.org/research/sota/city-rankings/states/california/riverside
2. James I. Riverside County air quality ranked among worst [Internet]. The Desert Sun. Available from: https://www.desertsun.com/story/news/environment/2014/04/30/american-lung-association-riverside-county-worst-us/8500589/
3. South Coast Air Quality Management District. The Southland's War on Smog: Fifty Years of Progress Toward Clean Air (through May 1997) [Internet]. South Coast Air Quality Management District. Available from: https://www.aqmd.gov/home/research/publications/50-years-of-progress
4. Wang S, Zhang J, Zeng X, Zeng Y, Wang S, Chen S. Association of Traffic-Related Air Pollution with Children's Neurobehavioral Functions in Quanzhou, China. Environmental Health Perspectives [Internet]. 2009 Oct 1;117(10). Available from: https://ehp.niehs.nih.gov/doi/full/10.1289/ehp.0800023
5. Chakraborty J, Zandbergen PA. Children at risk: measuring racial/ethnic disparities in potential exposure to air pollution at school and home. J Epidemiol Community Health. 2007 Dec;61(12):1074–9.
6. Liu J, Lewis G. Environmental Toxicity and Poor Cognitive Outcomes in Children and Adults. J Environ Health. 2014;76(6):130–8.
7. Reichmuth D. Inequitable Exposure to Air Pollution from Vehicles in California [Internet]. Massachusetts Institute of Technology; 2019 Jan. (Union of Concerned Scientists).

Available from:
https://www.ucsusa.org/resources/inequitable-exposure-air-pollution-vehicles-california-2019

8. Scharber H, Lucier C, London B, Rosofsky A, Shandra J. The consequences of exposure to developmental, neurological, and respiratory toxins for school performance: a closer look at environmental ascription in East Baton Rouge, Louisiana. Popul Environ. 2013 Dec 1;35(2):205–24.
9. Pastor M, Morello-Frosch R, Sadd JL. Breathless: Schools, Air Toxics, and Environmental Justice in California. Policy Studies Journal. 2006;34(3):337–62.
10. US EPA. EJSCREEN: Environmental Justice Screening and Mapping Tool [Internet]. US EPA. 2014. Available from: https://www.epa.gov/ejscreen
11. Burrough, P. A., Lloyd, C. D., & MacDonnell, R. A. (2015). *Principles of geographical information systems*. Oxford Univ. Press.