POLICY BRIEF
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RURAL & MINORITY Health Research Center

Assessing Geographic Variability in Key Indicators of Air Quality: A Rural vs. Urban Comparison of Pollution and Socio-Economic Factors

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Key Points:

Particulate Matter 2.5 (PM2.5)

- Rural census tracts had significantly lower levels of PM2.5 than urban tracts in the majority of EPA regions in all years investigated (2010, 2014, and 2019).
- Census tracts with a larger proportion of racial minoritized residents had significantly higher levels of PM2.5 in all years investigated.
- Census tracts with lower educational attainment had significantly higher levels of PM2.5 in all years investigated.

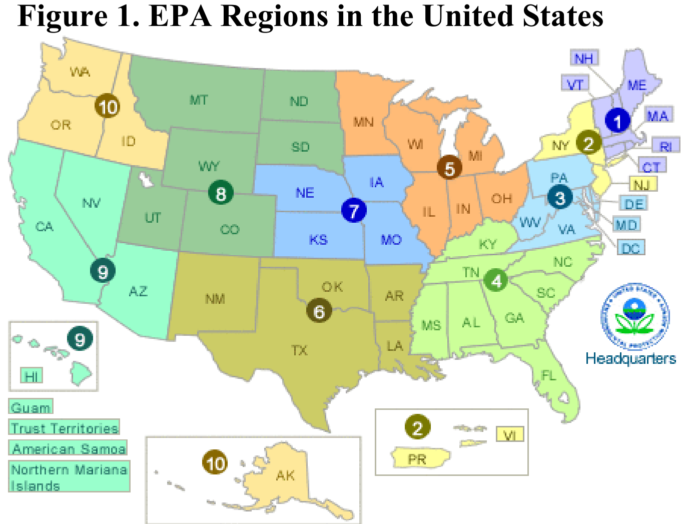
Ozone

- Rurality was generally not significantly associated with ozone levels in all years investigated (2010, 2014, and 2019). However, there were three exceptions to this rule: ozone was significantly higher in rural areas in region 9 in 2010 and significantly lower in rural areas in region 8 in 2014 and region 1 in 2019.
- In all three years evaluated, recreation counties had significantly lower levels of ozone than nonspecialized counties (reference level), counties with lower education had significantly higher levels of ozone, and counties with higher retirement had significantly higher levels of ozone.

INTRODUCTION

Exposure to polluted air varies across geography and the characteristics of communities and surrounding land.[1,2] This includes variation in topography, e.g., valleys surrounded by mountains like Los Angeles, topographic bowls such as Mexico City, etc. It also includes proximity of communities and people groups to industrial sources among other community complexities that contribute to harmful and hazardous environmental exposures. Furthermore, exposure to polluted air can lead to significant acute and chronic health issues including mental and physical effects, i.e., acute myocardial infarction, COPD, anxiety, etc. Mental and physical health stresses can be transient or cumulative depending on exposure frequency, namely whether contamination is prolonged or event/disaster-related (e.g., hurricanes, tornados, industrial spills, etc.).[3] Using data from the Centers for Disease Control and Prevention's National Environmental Public Health Tracking Program, prior research found that noncore (rural) counties had a lower mean number of ozone days (where daily averages of ground-level ozone concentration exceed the national standard) and lower average fine particulate matter air pollution levels (i.e., better air quality). The national standard for the

Figure 1. EPA Regions in the United States



Map retrieved from EPA. Source: https://www.epa.gov/risk/where-you-live-risk-

PM2.5 threshold for public health protection is an annual average that exceeds 12.0 μg/m^3.

Another study by Tessum et al.[4] found that fine particulate air pollution (PM2.5) was consistently more likely to impact racial/ethnic minorities in the U.S. in both urban and rural areas. PM2.5 is defined as fine inhalable particles that are 25 micrometers and smaller. The connection of PM2.5 to adverse health outcomes like asthma, lung cancer, cardiovascular disease, etc. warrant greater investigation of who is exposed and where. Yet little is known about regional differences or spatial variation in air quality over time. Given the differing economies and infrastructure present at the local level throughout the U.S., research examining exposure to polluted air at a more granular spatial level is needed. Therefore, the purpose of this study is to examine rates of air pollution between rural and urban census tracts and to examine urban-rural disparities in exposure to polluted air varied across Environmental Protection Agency (EPA)-defined regions (see Figure 1). Using air quality monitoring station data from the EPA's Air Quality System (AQS) web portal for the years 2000 to 2020, we examined variations of PM2.5 and ozone levels in the air at the census tract level.

METHODS

Air quality monitoring station locations and outcomes data were downloaded from the Environmental Protection Agency's (EPA) Air Quality System (AQS) web portal for years 2000 to 2020. A spatial interpolation process was then used to assign every census tract across the contiguous U.S. with an annual mean concentration estimate of PM2.5 and ozone. The results of the interpolation were linked with a variety of other variables (see Table 2) and then run through a regression model to test for statistical associations with rurality and EPA regions. A ten-year perspective was chosen between 2010 and 2019 to assess recent associations using incremental years (2010, 2014, and 2019) to evaluate trends. The incremental years were assessed as opposed to year-to-year changes as the latter were concluded to be less essential considering the computationally heavy models. Year 2020 was excluded from the analysis due to the potential economic and social impacts the pandemic may have had on pollutant concentrations and corresponding exposures.

In this study, minoritized refers to persons from traditionally marginalized racial groups exclusive of ethnicity. Therefore, persons who identified as Hispanic and white or white-alone are not classified as minoritized, and all other identities are classified as minoritized.

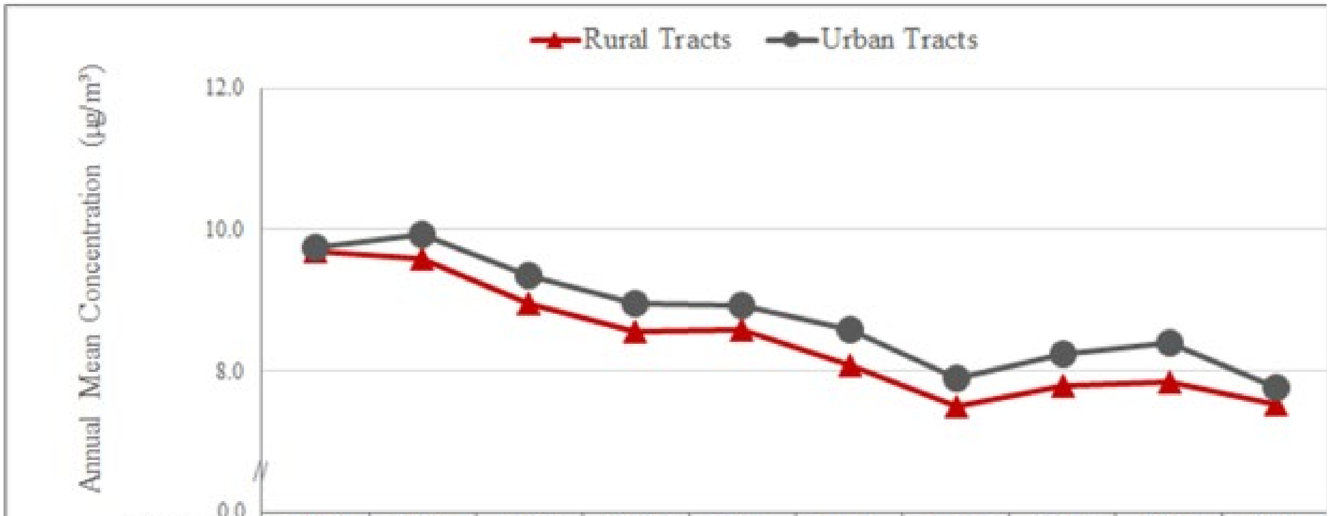
RESULTS

Rural census tracts had significantly lower levels of PM2.5 than non-rural tracts in most EPA regions in all years (2010, 2014, and 2019) after controlling for other factors. No statistically significant differences in PM2.5 levels were observed between rural and urban tracts in region 2 (2010 only), regions 5-7 (2014 only), and region 10 (2019 only).

Overall, census tracts with lower educational attainment had significantly higher concentrations of PM2.5. Census tracts that were proximate to industrial sites that require a risk management plan with the EPA also had significantly higher concentrations of PM2.5. Census tracts with economic and social effects related to farming, mining, manufacturing, federal/state government presence, and recreation also had significantly higher concentrations of PM2.5. Economic and social effects were allocated according to the U.S. Department of Agriculture's Economic Research Service and their county typology codes. Conversely, census tracts with more minoritized residents had significantly higher PM2.5 levels. Generally, rurality was not significantly associated with ozone levels in any year after controlling for all other factors.

However, there were three exceptions to this rule: increased ozone concentrations were significant in rural areas in region 9 in 2010, and decreased concentrations were significant in rural areas in region 8 in 2014 and region 1 in 2019. In all three years evaluated, recreation counties had significantly lower levels of ozone than nonspecialized counties (reference level), counties with lower education had significantly higher levels of ozone, and counties with higher retirement had significantly higher levels of ozone. Figure 2 (page 3) shows the interpolation estimates for PM2.5 annual mean concentrations among urban and rural census tracts from 2010 through 2019.

Figure 2. Annual Interpolated Mean Concentrations of PM 2.5 in Rural and Urban Census Tracts

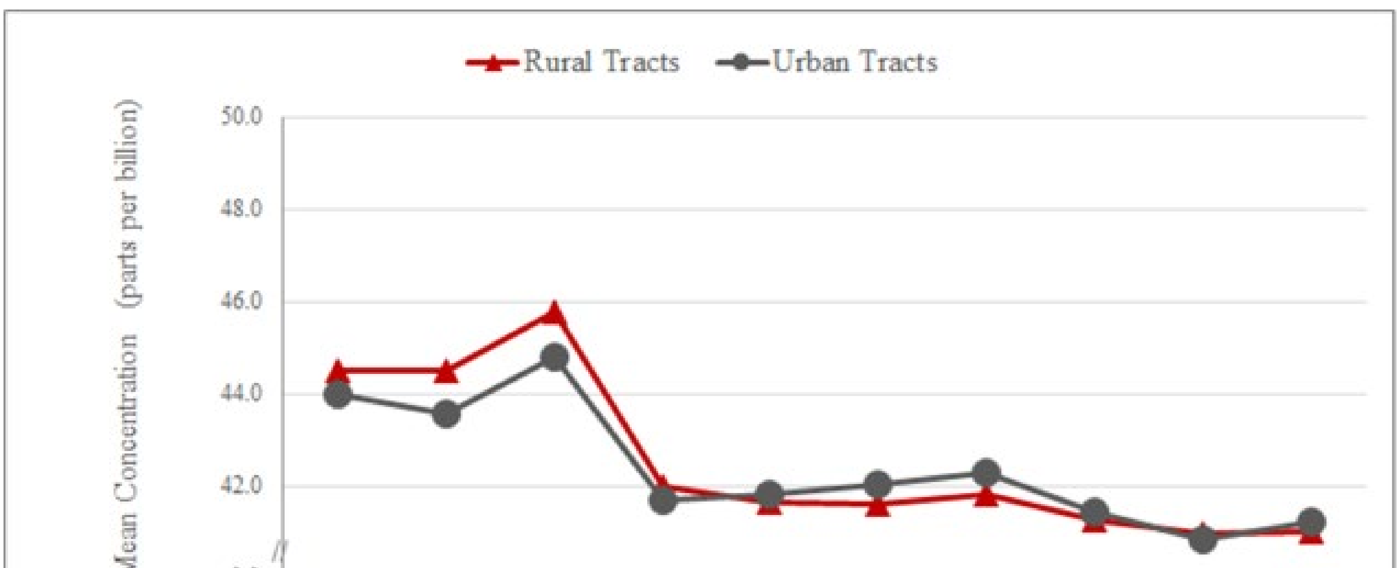


Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Rural Tracts	9.7	9.6	9.0	8.6	8.6	8.1	7.5	7.8	7.9	7.5
Urban Tracts	9.7	9.9	9.4	8.9	8.9	8.6	7.9	8.3	8.4	7.8

Overall, decreases in PM2.5 concentrations can be observed for both urban and rural areas during this period. Among all years assessed, urban census tracts had higher annual concentrations than rural except for 2010 when they were equal.

Similarly, the results for ozone presented in Figure 3 show a general decreasing trend during this period. However, urban and rural estimates varied. Between 2010 and 2013, ozone levels were higher on average in rural census tracts. Levels were higher in urban tracts between 2014 and 2017 and alternated between 2018 and 2019.

Figure 3. Annual Interpolated Mean Concentrations of Ozone in Rural and Urban Census Tracts



Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Rural Tracts	44.5	44.5	45.8	42.0	41.6	41.6	41.8	41.3	41.0	41.0
Urban Tracts	44.0	43.6	44.8	41.7	41.8	42.0	42.3	41.4	40.9	41.2

Figures 4 and 5 below show the results of the interpolation by EPA region for years 2010, 2014, and 2019. An estimate for all census tracts in the contiguous U.S. is provided. Note, both PM2.5 and ozone show decreasing trends during this period with localized hot spots of higher concentrations in later years. Hot spots for PM2.5 were observed in EPA regions 4, 5, and 9 across all years with peaks in Southern California and Illinois in 2019. Ozone hot spots trended towards western states in EPA regions 6, 8, and 9 across all years with the most recent peak concentrations localizing in Southern California in 2019.

Figure 4. PM2.5 Concentrations (µg/m³) for Census Tracts by EPA Region

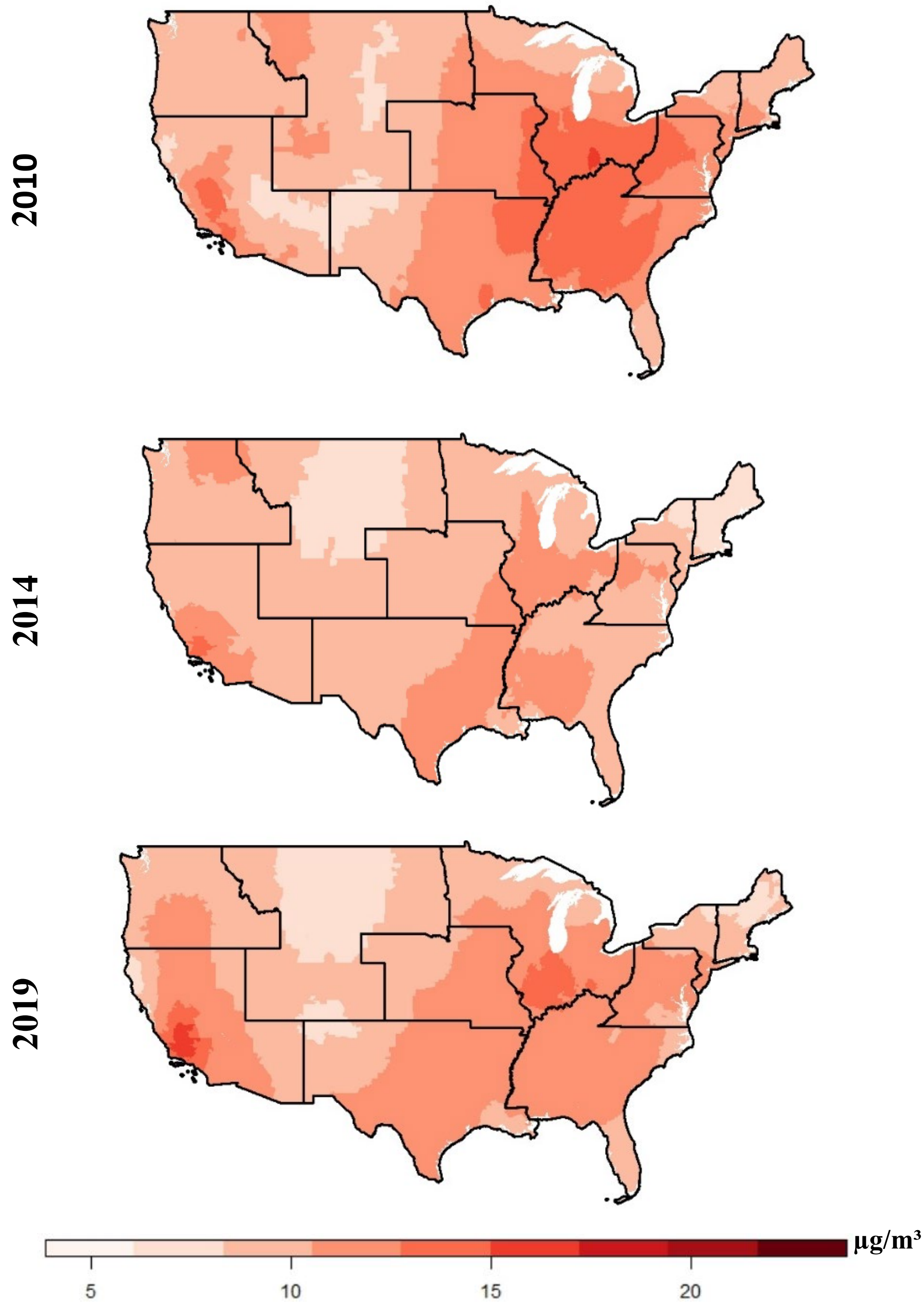
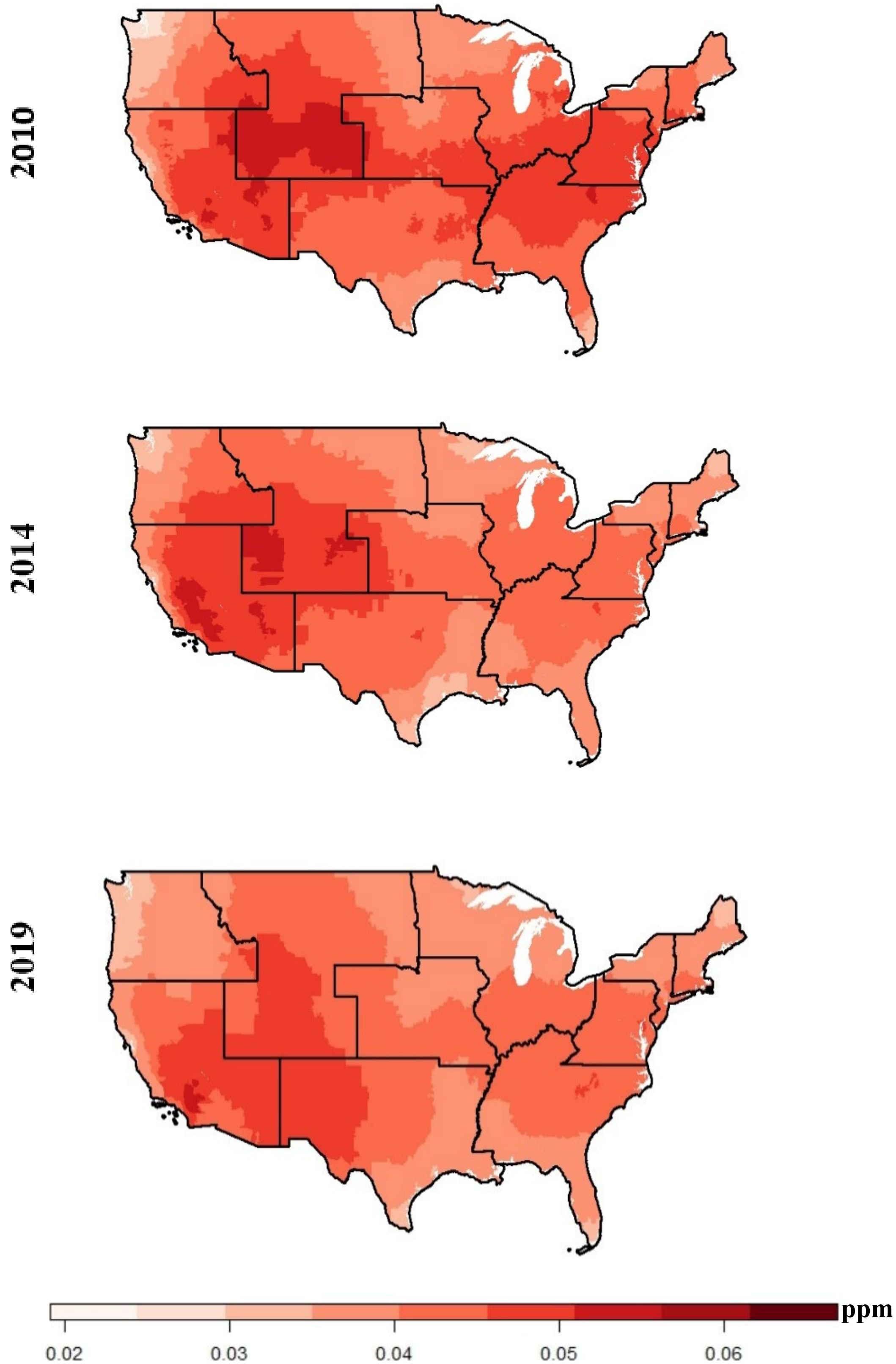


Figure 5. Ozone Concentrations (ppm) for Census Tracts by EPA Region



DISCUSSION

Health impacts from exposure to PM2.5 are well documented.[5] Smaller particles in the air pose a risk as they can enter the deep parts of the lungs as well as the bloodstream.[6] PM2.5 can cause diseases like asthma, COPD, and lung cancer.[7] It can also lead to hospital admissions and deaths from diseases such as asthma, COPD, cardiovascular disease, and some cancers, e.g., lung cancer.[8,9,10] Similarly, ozone exposure can lead to asthma and make respiratory symptoms worse. People who are more at risk from ozone exposure include those who have asthma or other lung diseases, older adults (relative to younger population groups in some studies; may also include specific age groups, i.e., those 65 years and older in other studies), people with outdoor occupations, as well as babies and children.[11]

Rural census tracts were identified with lower levels of PM2.5 compared to urban tracts. However, lower levels of ozone were not identified to be associated with either rural or urban census tracts aside from the exceptions identified above. Community characteristics associated with higher levels of PM2.5 included low employment and minoritized race. Census tracts with higher proportion of non-minoritized residents, on average, had lower levels of PM2.5. This parallels substantial literature on environmental justice showing that communities with a greater density of minoritized residents are exposed to more air pollution.[12] A breakdown by quartile of proportion of non-minoritized residents with corresponding PM2.5 and ozone concentrations for 2010, 2014, and 2019 is provided in Table 1. Significant characteristics associated with ozone across all years investigated include recreation, education, and retirement.

Annual mean concentrations for PM2.5 and ozone have been trending downward over the last decade. Although these trends are headed in a direction that is positive for public health nationally, there remain significant burdens related to poor air quality, especially along the stress-exposure disease framework with place-based factors i.e., communities most proximate to industrial sites, as well as race, education, and income.

Despite downward trends nationally, recent clusters for increased levels of PM2.5 were observed primarily along the west coast and other western regions of the state primarily California, Oregon, and Washington. The results of this investigation support this as EPA Region 9 (CA, NV, and AZ) was assessed to have the highest levels of PM2.5 from 2010, 2014, and 2019. Drought conditions with correlations to climate change have created a context for increased propensity of wildfires and the cascading impacts related to poor air quality which in turn leads to adverse respiratory health impacts.[13, 14] The prime location for these areas is rural. The Rim Fire of 2013 in northern California was a case where particulate matter from the ash impacted the Hetch Hetchy aqueduct that fed the Bay Area. This aqueduct provided drinking water for 2.6 million customers.[15] Future cascading events between drought and wildfire, catalyzed by climate change, are of particular interest for both air and water quality in the rural context with additional interactions with urban populations.

The findings support the correlation of poverty, education, income, and race with poor air quality especially related to PM2.5. These are relevant from a national perspective as the investigation assessed the contiguous U.S. These are also consistent with investigations in locations near toxic release sites where relationships with sociodemographic characteristics such as race and poverty have been explored. Black persons have been identified to be more likely than their white counterparts to live below the poverty line, live closer to an industrial emissions source, and live closer to multiple industrial emissions sources.[16] Additionally, low socioeconomic status including indicators that contained education and income have been associated with higher levels of PM2.5, as well as, adverse health outcomes such as cardiovascular events.[17]

Mailloux et al. estimate that eliminating energy-related emissions at a national level could prevent 53,200 premature deaths and enable around $608 billion in benefits by avoiding morbidity and mortality associated with PM2.5.[18] This estimates the public health benefits that an ambitious national focus on clean energy and climate change policy could have. For example, some states like California and Michigan are calling for economy-wide carbon neutrality extending beyond specific industries like automobiles. Most of the benefits identified above, where emissions are removed from the energy sector, would remain in that area providing local benefits from local action.

Environmental justice (EJ) is defined by the EPA as “the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income…[where] everyone enjoys the same degree of protection from environmental and health hazards and equal access to the decision-making process to have a healthy environment in which to live, learn, and work.”[19] Engagement with EJ communities that are proximate to industrial sites and other emissions sources, e.g., highways, ports, railyards, etc. can be supported by activities including adding air quality monitors in these locations and engaging community members to play a role in the maintenance, data tracking, and analysis. A local level approach to air pollution improvements is a crucial step for policy efforts. The work of citizen scientists among EJ communities has demonstrated success in this area.[20] This can build awareness around pollution exposure and build capacity to make improvements by eliminating exposures through adequate policy protections and technological enhancements for cleaner energy.

The limitations of this investigation are based primarily on the availability of the data. Reduced validity of the concentration estimates may be related to the precision of the interpolation of pollution concentrations for each census tract in the contiguous U.S. When compared to more sophisticated models, i.e. the Community Multiscale Air Quality Modeling System (CMAQ), the results of the interpolation do not include the added variability of pollutant deposition, meteorological inputs, local topographical influence on atmospheric transport, etc. However, not all years or pollutants of interest were available within models like CMAQ which was the rationale for reliance on the interpolated concentrations. Additionally, the findings from the interpolation do not include exposure estimates of populations to the pollutants of interest, only local concentrations. Assumptions of validity include using a mixed model of both county-level and census tract-level variables as well as variables available for only certain years. It should be noted that variables of interest were utilized where available for both spatiality and temporality. Future studies should examine disparities across economic and social community characteristics within EPA regions or other geographic boundaries.

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APPENDIX

Technical Notes

The AQS provides access to the air pollution data collected by various air quality control agencies from thousands of monitors across the United States. Data for the EPA's criteria air pollutants (carbon monoxide, lead, nitrogen dioxide, ozone, PM2.5, and sulfur dioxide) were downloaded for the years 2000 to 2020. The geographic coverage of the data consisted of the contiguous United States.

Each row in the AQS dataset represented a specific monitoring site with a variety of corresponding variables including the sample duration the respective pollutant was measured, units of measurement, the annual average concentration, number of times in the year the monitoring site had a measurement above the EPA's threshold standard, etc.

The levels of the RUCA primary code classification were grouped into rural and urban where any census tract that was less than or equal to three was classified as urban and any census tract above three was rural. Each monitoring site was associated with the nearest RUCA code from the Economic Research Service's 2000 and 2010 RUCA datasets. EPA region was also appended to the dataset and allocated for each monitoring site.

Air quality measurements for each census tract across the U.S were generated using spatial interpolation. The results were then linked with variables to control for statistical associations. Assessing each year across the study period was not necessary for the analysis. Thus, different points in time over the last 10 years were selected to acquire a valid perspective of trends and sample size: 2010, 2014, and 2019.

The data was spatially interpolated using the kriging method. The results were then compared to the EPA's Community Multiscale Air Quality (CMAQ) model to assess for inconsistencies. The benefits of the interpolated results allowed for assessing all six criteria air pollutants over the entire study period from 2000 to 2020 where the CMAQ model is only available as recent as 2017 and for fewer air pollutants.

A Bayesian model was used where statistical importance was assessed using 95% credible intervals. Data sources for the covariates include the United States Department of Agriculture's Economic Research Services County Typology codes for categories of economic dependence i.e. farming, manufacturing, mining, etc. Also included were variables from the American Community Survey (ACS) related to education, race, and income. Finally, an additional variable of interest was exposure to proximate industrial pollution that was sourced from the EPA's EJ Screen dataset. Proximity is defined in the EPA EJ Screen dataset as the count of RMP facilities within 5km (or nearest one beyond 5km) each divided by distance in km. Not all variables were available at the census tract level or for all years used in the model. Spatially, county-level data was linked to the census tracts that existed within. Temporally, years for data availability were linked to the closest year available.

Table 1. Quartiles of Proportion of White Residents by Mean and Standard Deviation of PM2.5 and Ozone, 2010, 2014, and 2019

PM2.5		**2010**			**2014**			**2019**	
	Proportion	**Mean**	**SD**	**Proportion**	**Mean**	**SD**	**Proportion**	**Mean**	**SD**
1st Quartile	0.62	10.194	1.644	0.62	9.261	1.534	0.61	8.068	1.105
Median	0.83	9.566	1.877	0.82	8.978	1.657	0.83	7.832	1.116
3rd Quartile	0.93	9.424	1.918	0.93	8.634	1.583	0.93	7.567	1.06
4th Quartile	1	9.762	1.954	1	8.563	1.548	1	7.431	1.1
Ozone		**2010**			**2014**			**2019**	
	Proportion	**Mean**	**SD**	**Proportion**	**Mean**	**SD**	**Proportion**	**Mean**	**SD**
1st Quartile	0.62	0.04365	0.005	0.62	0.04157	0.004	0.61	0.04142	0.004
Median	0.83	0.04379	0.005	0.82	0.04203	0.004	0.83	0.04146	0.004
3rd Quartile	0.93	0.044	0.005	0.93	0.04195	0.004	0.93	0.04106	0.004
4th Quartile	1	0.045	0.004	1	0.04162	0.003	1	0.04087	0.003

Table 2. Summary of variables assessed

Variable	2010	2014	2019
Non-overlapping economic-dependence county indicator (farm-dependent, mining-dependent, manufacturing-dependent, etc.)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Low education (at least 20% residents with no HS diploma or equivalence)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Low employment (less than 65% of residents were employed between 2008-2012)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Proportion of population loss (number of residents declined in US Census between 1990-2000 & 2000-2010)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Retirement destination (increase in number of residents 60 years or older by 15% between 2000-2010)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Persistent Poverty (at least 20% of residents were poor 1980, 1990, and 2000)	2015 CountyTypologyCodes.csv file downloaded from https://www.ers.usda.gov/data-products/county-typology-codes.aspx	Same as 2010	Same as 2010
Proportion with a bachelor's degree	ACS 2010	ACS 2014	ACS 2019
Proportion of the population which is white	ACS 2010	ACS 2014	ACS 2019
Gini Income Inequality	ACS 2010	ACS 2014	ACS 2019
Binary indicator of rurality	Primary RUCA Code 2010 in the ruca2010revised.csv file, defined to be rural if the code is strictly greater than 3.	Same as 2010	Same as 2010
EPA Region	N/A	Same as 2010	Same as 2010
PRMP	EJ Screen data retrieved from: https://www.epa.gov/ejscreen/download-ejscreen-data	Same as 2010	Same as 2010

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