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Key Points:

- Between 2010 and 2019, $PM_{2.5}$ levels were consistently lower in rural communities than in urban communities across the United States
- High percentage Black communities had significantly higher $PM_{2.5}$ pollution levels in both rural and urban census tracts
- Greater protection from air pollution for socially disadvantaged communities in both rural and urban settings is warranted

Supporting Information:

Supporting Information may be found in the online version of this article.

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Geographic Variations in Urban-Rural Particulate Matter ($PM_{2.5}$) Concentrations in the United States, 2010–2019

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Abstract Fine particulate matter 2.5 ($PM_{2.5}$) is a widely studied pollutant with substantial health impacts, yet little is known about the urban-rural differences across the United States. Trends of $PM_{2.5}$ in urban and rural census tracts between 2010 and 2019 were assessed alongside sociodemographic characteristics including race/ethnicity, poverty, and age. For 2010, we identified 13,474 rural tracts and 59,065 urban tracts. In 2019, 13,462 were rural and 59,055 urban. Urban tracts had significantly higher $PM_{2.5}$ concentrations than rural tracts during this period. Levels of $PM_{2.5}$ were lower in rural tracts compared to urban and fell more rapidly in rural than urban. Rural tract annual means for 2010 and 2019 were 8.51 [2.24] μg/m^3 and 6.41 [1.29] μg/m^3, respectively. Urban tract annual means for 2010 and 2019 were 9.56 [2.04] μg/m^3 and 7.51 [1.40] μg/m^3, respectively. Rural and urban majority Black communities had significantly higher $PM_{2.5}$ pollution levels (10.19 [1.64] μg/m^3 and 9.79 [1.10] μg/m^3 respectively), in 2010. In 2019, they were: 7.75 [1.1] μg/m^3 and 7.09 [0.78] μg/m^3, respectively. Majority Hispanic communities had higher $PM_{2.5}$ levels and were the highest urban concentration among all races/ethnicities (8.01 [1.73] μg/m^3), however they were not the highest rural concentration among all races/ethnicities (6.22 [1.60] μg/m^3) in 2019. Associations with higher levels of $PM_{2.5}$ were found with communities in the poorest quartile and with higher proportions of residents age<15 years old. These findings suggest greater protections for those disproportionately exposed to $PM_{2.5}$ are needed, such as, increasing the availability of low-cost air quality monitors.

Plain Language Summary $PM_{2.5}$ is a well-known air pollutant that impacts human health. However, little is known about how it differs between urban and rural areas in the United States (U.S). This study investigated these differences between 2010 and 2019 at a level that had not been assessed before across the United States. Rural areas generally had lower $PM_{2.5}$ levels compared to urban areas and the pollution decreased faster in rural areas during this time. Both rural and urban areas with higher proportions of residents that are Black, Hispanic, and in poverty had higher $PM_{2.5}$ levels. There were no consistent patterns between the age distribution of urban or rural census tracts and $PM_{2.5}$ levels.

1. Introduction

1.1. $PM_{2.5}$ and Public Health

Fine particulate matter, also known as Particulate Matter 2.5, or $PM_{2.5}$, is made of inhalable products measured at 2.5 μm or smaller. This is a size-based definition alone and does not pertain to its chemical makeup. $PM_{2.5}$ is an air pollutant consisting of particles that can penetrate deep into the lungs and even into the bloodstream, and is associated with serious health problems (Particle Pollution|Air|CDC, 2023). Particulate matter results from emissions from power plants, industrial sites, cars/vehicles, wildfires, sources linked to agriculture and construction, among others (Tucker, 2000). Exposure to $PM_{2.5}$ has been linked to a wide range of adverse health outcomes, including respiratory and cardiovascular diseases (Chalbot et al., 2014; Xi et al., 2022), stroke (Bai et al., 2022), adverse birth outcomes (Payne-Sturges et al., 2022), and even premature death (Chalbot et al., 2014). Specifically, it is estimated that 100,000 to 200,000 excess deaths occur annually in the United States are associated with air pollution exposures (Burnett et al., 2018). Despite the well-documented health risks by $PM_{2.5}$, according to the American Lung Association (ALA), 119.6 million of United States residents (almost 36%) are exposed to levels of $PM_{2.5}$ or ozone on a daily basis that are deemed unhealthy and score a failing grade on the ALA's State of the Air Report (American Lung Association, 2023). Currently, the United States Environmental Protection Agency (EPA) defines the primary standard for $PM_{2.5}$ at 9.0 μg/m^3 (annual average) and 24-hr standard at a level of 35 μg/m^3. As a result of state and federal regulations and technological advancements to

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limit $PM_{2.5}$ emissions and subsequent exposure (e.g., smokestack scrubbers, idle-reduction technology, prevalence of gas-electric hybrid vehicles, etc.) (US EPA, 2015), ambient air quality has improved significantly in the past three decades (Lim et al., 2020). However, the extent to which $PM_{2.5}$ exposures vary across location and time remains uncertain.

1.2. Rural-Urban Disparities in $PM_{2.5}$-Related Health Outcomes

Few studies have examined variation in $PM_{2.5}$ by urban-rural location, with many studies conducted in urban areas and few in rural areas (Garcia et al., 2016). Factors such as local industries, land use patterns, and population mobility differ between urban and rural settings (US EPA, 2017). In rural areas, $PM_{2.5}$ has been found to be associated with all-cause mortality, while there were only mild associations with urban areas (Garcia et al., 2016). Understanding the specific dynamics of $PM_{2.5}$ pollution in rural and urban United States is essential for tailoring effective mitigation strategies and policies to address the unique challenges faced by each community.

1.3. Rural-Urban $PM_{2.5}$ Statistics and Potential Factors for Differences

Land use patterns and socioeconomic factors significantly influence $PM_{2.5}$ exposure types across rural-urban areas, where the rural poor appear to be disproportionately burdened (Hendryx et al., 2010; Rogalsky et al., 2014). Typically referred to as household air pollution (HAP), rural $PM_{2.5}$ exposure in low and middle income countries has traditionally been linked to biomass burning for cooking and heating (Siddharthan et al., 2018). Similarly, $PM_{2.5}$ exposures in rural areas in the United States have been linked to wood and coal burning for residential heating (Rogalsky et al., 2014). Hendryx et al. (2010) found that rural areas contain fewer sources of air pollution such as power plants per county compared to urban areas, however they still contain thousands of both air and water pollution sources. For example, they observed 931 fossil fuel burning sites in the U.S, 16,574 Toxic Release Inventory sites, 14,276 Aerometric Information Retrieval System sites, and 34,214 Permit Compliance System sites, totaling 65,055 EPA-designated pollution sites in the rural context. Additional sources of $PM_{2.5}$ in the rural United States are linked to ambient sources, including coal mining and agricultural production (Hendryx et al., 2010). As mentioned above, $PM_{2.5}$ sources in the urban context are often linked to fossil fuel combustion from power generation, industry, and transportation-related sources (Cohen et al., 2004) and have received significant attention in the literature.

The current study investigated the ambient air concentrations of $PM_{2.5}$ at the census tract level from 2010 through 2019 across the United States The focus of this study was to assess rural and urban differences and trends with ambient $PM_{2.5}$ during this period and to compare these by community sociodemographic characteristics. This study will fill the evidence gap on the national urban-rural and community-level air quality differences and trends in concentration. Recent advances in modeled data for $PM_{2.5}$ enabled this study, providing valid $PM_{2.5}$ estimates at a meaningful geographic granularity (Hammer et al., 2020; van Donkelaar et al., 2019).

2. Methods

2.1. Data Sources

The data used was sourced from the Agency for Healthcare Research and Quality (AHRQ)'s database on Social Determinants of Health (SDOH) (Agency for Healthcare Research and Quality, Rockville, MD, 2023), created from multiple data sources from various domains as a means to facilitate health research and analysis. The specific SDOH database columns and their respective descriptions utilized for the analysis and mapping are listed in the Supplemental Information, Table 1. Additionally, estimates for census tract levels of $PM_{2.5}$ were accessed from the AHRQ SDOH Database, using the Washington University Saint Louis—Atmospheric Composition Analysis Group's (WUSTL) modeled estimates of $PM_{2.5}$ (Hammer et al., 2020; van Donkelaar et al., 2019).

2.2. Measurement

Annual mean concentrations of $PM_{2.5}$ for each census tract in the contiguous United States from 2010 to 2019 were downloaded from the AHRQ database. The focus of our study was air quality surveillance in urban and rural areas, which was determined based on census tracts. The levels of rurality were established using the United States Department of Agriculture's 2010 Rural-Urban Commuting Area (RUCA) codes. For the purposes of this investigation, RUCA codes were categorized into two groups: urban (RUCA 1–3: various types metropolitan

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Table 1
Variations in $PM_{2.5}$ Concentration ($\mu g/m^3$) by Community Characteristics in Urban and Rural Census Tracts, 2010 and 2019

	2010		2019		Annual change from 2010 to 2019		
Community characteristics	Urban	Rural	Urban	Rural	Urban	Rural	*P* values for differential trends
Number of Census Tracts	59,065	13,474	59,055	13,462			
	Annual mean (SD) of $PM_{2.5}$ concentration ($\mu g/m^3$)		Annual mean (SD) of $PM_{2.5}$ concentration ($\mu g/m^3$)				
National	9.56 (2.04)	8.51 (2.24)	7.51 (1.40)	6.41 (1.29)	−2.01	−2.08	<0.0001
Top Quartile Communities by Race/Ethnicity							
Black (≥14.75%)	10.19 (1.64)	9.79 (1.1)	7.75 (1.09)	7.09 (0.78)	−2.41	−2.71	<0.0001
Hispanic (≥17.76%)	9.6 (2.22)	7.25 (2.29)	8.01 (1.73)	6.22 (1.60)	−1.59	−1.06	<0.0001
American Indian and Alaska Native (≥0.59%)	9.06 (2.24)	7.42 (2.21)	7.46 (1.6)	5.93 (1.29)	−1.64	−1.47	<0.0001
Other Race (≥13.62%)	9.51 (2.13)	7.95 (2.18)	7.71 (1.53)	6.38 (1.27)	−1.78	−1.59	<0.0001
Quartile of Poverty Rates							
Quartile 1 (≤5.87%)	9.3 (1.96)	8.13 (2.29)	7.23 (1.3)	6.14 (1.35)	−2.04	−1.95	0.01
Quartile 2 (5.88%–11.48%)	9.4 (2.08)	8.18 (2.28)	7.4 (1.37)	6.18 (1.3)	−2.01	−1.98	0.16
Quartile 3 (11.49%–20.19%)	9.6 (2.07)	8.41 (2.25)	7.59 (1.44)	6.37 (1.23)	−2.05	−2.07	0.24
Quartile 4 (20.20%–100.0%)	10 (2.01)	9.01 (2.12)	7.88 (1.4)	6.71 (1.22)	−2.12	−2.32	<0.0001
Quartile of % Residents Age<15							
Quartile 1 (≤15.99%)	9.42 (2.02)	7.94 (2.28)	7.41 (1.37)	6.06 (1.26)	−1.99	−1.88	<0.0001
Quartile 2 (16.00%–19.49%)	9.5 (2.02)	8.63 (2.16)	7.37 (1.34)	6.42 (1.18)	−2.12	−2.22	<0.0001
Quartile 3 (19.50%–23.12%)	9.55 (2.01)	8.85 (2.12)	7.49 (1.37)	6.57 (1.19)	−2.12	−2.28	<0.0001
Quartile 4 (23.13%–78.95%)	9.76 (2.1)	8.5 (2.41)	7.75 (1.46)	6.54 (1.45)	−1.98	−1.94	0.08
Quartile of % Residents Age>65							
Quartile 1 (≤8.60%)	9.74 (2.09)	7.94 (2.56)	7.85 (1.48)	6.41 (1.58)	−1.95	−1.7	<0.0001
Quartile 2 (8.61%–12.47%)	9.53 (2.05)	8.7 (2.31)	7.54 (1.38)	6.65 (1.35)	−2.06	−2.14	0.002
Quartile 3 (12.48%–16.57%)	9.52 (1.99)	8.81 (2.15)	7.32 (1.3)	6.58 (1.17)	−2.16	−2.29	<0.0001
Quartile 4 (16.58%–100.0%)	9.39 (2.01)	8.28 (2.2)	7.22 (1.30)	6.16 (1.22)	−2.05	−2.02	0.07

areas) and rural (RUCA 4–10: various types of micropolitan, small town, and rural areas). Each census tract was coded according to its RUCA allocation. The covariates used included race/ethnicity, poverty level, age groups, and a variable combining socially disadvantaged population segments (defined below).

2.3. Analysis

$PM_{2.5}$ concentrations in urban versus rural census tracts were compared for each year from 2010 to 2019 using *t*-tests. Trends in $PM_{2.5}$ concentrations between 2010 and 2019 in urban versus rural areas were assessed with a Bayesian spatial model. This model assumes that conditional on the model parameters, the $PM_{2.5}$ concentration in tract s and year t independently follow a normal distribution with mean

$$\mu_{st} = \beta_0 + \beta_1 r_s + \beta_2 t + \beta_3 r_s t + \phi_s$$

and variance σ^2. Equivalently, the $PM_{2.5}$ concentration in tract s and year t, $y_{st} = \mu_{st} + \epsilon_{st}$, where the ϵ_{st} terms independently follow a normal $(0, \sigma^2)$ distribution. Here ￼, where S is the number of census tracts and $t = 2010, 2011, \ldots, 2019$. Here r_s is equal to 1 if tract s is rural and

$$\phi = (\phi_1, \phi_2, \ldots, \phi_S)'$$

is a vector of spatial random effects having a conditional autoregressive (CAR) prior, which is included to account for the spatial dependence in $PM_{2.5}$ concentrations between tracts. The model was fitting using integrated nested LaPlace approximation using the R-INLA package. All other model parameters were assumed to follow the default prior distributions in the R-INLA package.

Herein, socially disadvantaged was defined as those segments of the population including racial minorities (Black, Hispanic, American Indian/Alaska Native and Other Race), an income to poverty ratio under 1.00, the percent of the population less than 15 years of age, and the percent of the population greater than 65 years of age. We used the American Community Survey variables to define race, which do not incorporate and combine ethnicity categories for Hispanic, Latino, or Spanish with other races. Other Race included Asian, Native Hawaiian and Other Pacific Islander, and some other race. Additionally, the term Hispanic included people who identified with at least one of the Hispanic or Latino categories, for example, Mexican, Chicano, Puerto Rican, Cuban, etc. Therefore, the Black category used in the analysis included non-Hispanic Black and Hispanic-Black. To compare $PM_{2.5}$ concentrations between socially disadvantaged rural versus socially disadvantaged urban tracts, a stratified analysis was performed. Comparisons between rural and urban tracts within strata were made using *t*-tests for 2010 and 2019. We defined four strata consisting of tracts with a high percentage of residents identifying as Black, Hispanic, American Indian/Alaska Native and Other Race. Each of these four strata consisted of tracts whose percent population in the given racial/ethnic category exceeded the 75th percentile taken across all tracts in the contiguous United States. Quartiles of the percent poverty level taken across all tracts in the contiguous United States were used to define four poverty strata. Quartiles of the percent of the population less than 15 years of age and quartiles of the percent of the population greater than 65 years of age were used to define eight age-distribution strata.

A trends analysis was performed using these strata. To control the different tracts that fell into each stratum in 2010 and 2019, the trends analysis was restricted to tracts which fell into each stratum in 2010. A linear mixed model was fitted to the $PM_{2.5}$ data from 2010 to 2019 for each stratum. Data from the intermediate years was not included in the model. The $PM_{2.5}$ concentration in tract s and year t was assumed to follow a normal distribution with mean

$$\mu_{st} = \beta_0 + \beta_1 r_s + \beta_2 y_t + \beta_3 r_s y_t + \psi_s$$

and variance σ^2; equivalently $y_{st} = \mu_{st} + \epsilon_{st}$, where the ϵ_{st} terms independently follow a normal $(0, \sigma^2)$ distribution. Here y_t is equal to 1 if $t = 2019$ and 0 if $t = 2010$, and $\psi = (\psi_1, \psi_2, \ldots, \psi_{S'})$ is a vector of independently and identically normally distributed tract-level random effects, where S' denotes the number of tracts in the given strata in 2010. We can therefore interpret β_2 as average change in $PM_{2.5}$ concentration in the strata's urban tracts between 2010 and 2019 and $\beta_2 + \beta_3$ as the average change for rural tracts. Note that as the model did not include data from 2011 to 2018; these coefficients should not be interpreted as the average *rate* of change between 2010 and 2019, but rather as the average total change between 2010 and 2019.

3. Results

3.1. Rural-Urban Differences in $PM_{2.5}$ Exposures and Trend Over Time

Over 2010–2019, $PM_{2.5}$ pollution levels were consistently lower in rural communities than in urban communities and decreased more rapidly in rural versus urban communities. In urban communities, $PM_{2.5}$ concentration declined from 9.56 μg/m^3 in 2010 to 7.51 μg/m^3 in 2019, while in rural communities it declined from 8.51 μg/m^3 to 6.41 μg/m^3 (Figure 1). This represents an overall relative decline of 21.4% in urban communities and 24.7% in rural communities between 2010 and 2019. Specifically, posterior mean slope (95% credible intervals) for urban communities was −0.235 (−0.236, −0.235) and it was −0.243 (−0.245, −0.241) for rural communities. Notably, both rural and urban communities experienced decreasing trends in $PM_{2.5}$ concentration until 2016, with a slightly flatter trend observed in 2016–2018 compared to 2010–2016. However, the decline continued in 2019.

Urban (blue) census tracts had significantly higher $PM_{2.5}$ concentrations than rural census tracts in every year, based on *t*-tests. Trends assumed linearity of $PM_{2.5}$ over time and have been adjusted for spatial correlations between census tracts, as explained in the text. We used 95% credible intervals and a significance level of $p < 0.05$. Detailed data points are available in Table S2 in Supporting Information S1.

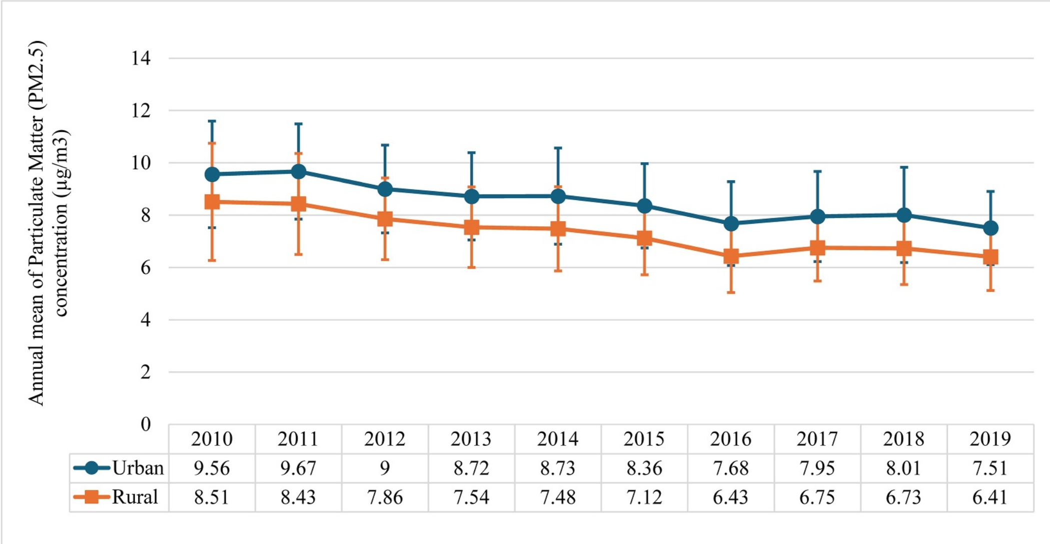

Figure 1. Rural-urban differences in the trends of the Particulate Matter ($PM_{2.5}$) concentration (µg/m^3).

3.2. Geographic Distributions of $PM_{2.5}$ Pollution

Maps were created using the census tract areas in combination with the corresponding year and annual mean $PM_{2.5}$ concentration levels (Figure S1 for 2010 and Figure S2 for 2019 in Supporting Information S1). Figure S3 (2019) in Supporting Information S1 shows both urban and rural census tracts using the same color scale to relate that air quality follows a broad regional pattern covering both urban and rural areas influenced by both geography and industry. The national trend shown between the 2010 and 2019 maps indicates that $PM_{2.5}$ concentration levels have decreased, indicating better air quality with reference to $PM_{2.5}$ over this decade. Figure 2a depicts this decreasing trend by showing the percent difference for $PM_{2.5}$ concentrations across census tracts from 2010 to 2019. Figures 2b and 2c show percent change of rural tracts only and urban tracts only, respectively. Note the predominant improvements east of the Mississippi River with several areas of increasing $PM_{2.5}$ concentrations in the Pacific Northwest and Southwest. Despite showing an increasing trend, these latter areas were still within the threshold below the national air quality standard for $PM_{2.5}$.

3.3. Differential Annual Trends by Community Characteristics in Rural and Urban Census Tracts

In 2010, high Black communities (high percentage was defined as those census tracts whose percent population in the Black racial/ethnic category exceeded the 75th percentile taken across all tracts in the contiguous United States), in both rural and urban census tracts, had significantly higher $PM_{2.5}$ pollution levels (mean [SD] 10.19 µg/m^3 [1.64] and 9.79 µg/m^3 [1.1] respectively (see Table 1)); than the national levels. Between 2010 and 2019, $PM_{2.5}$ pollution declined more rapidly in high Black communities than in other communities, particularly in rural, high Black communities (annual change of −2.71 µg/m^3, $p < 0.0001$). High percentage Hispanic populations had higher $PM_{2.5}$ levels and were the highest urban concentration among all races/ethnicities (8.01 [1.73] µg/m^3), however they were not the highest rural concentration among all races/ethnicities (6.22 [1.60] µg/m^3) in 2019. By poverty level (defined as those census tracts with an income to poverty ratio under 1.00), communities in the poorest quartile had the highest levels of $PM_{2.5}$ pollution, with the greatest rural-urban differences in the pollution levels (Urban 2010: 10 [2.01] µg/m^3, Urban 2019: 7.88 [1.4] µg/m^3), (Rural 2010: 9.01 [2.12] µg/m^3, Rural 2019: 6.71 [1.22] µg/m^3). The p-value for the differential trend between 2010 and 2019 was <0.0001. The lowest $PM_{2.5}$ concentrations among the four poverty strata were in the least poor (quartile 1) rural communities (2010: 8.13 [2.29] µg/m^3, 2019: 6.14 [0.35] µg/m^3). Rural-urban differences in $PM_{2.5}$ pollution levels were similar across communities by the proportions of residents age<15 years old, with rural communities consistently experiencing less pollution by $PM_{2.5}$ than urban communities, regardless of the mix of age.

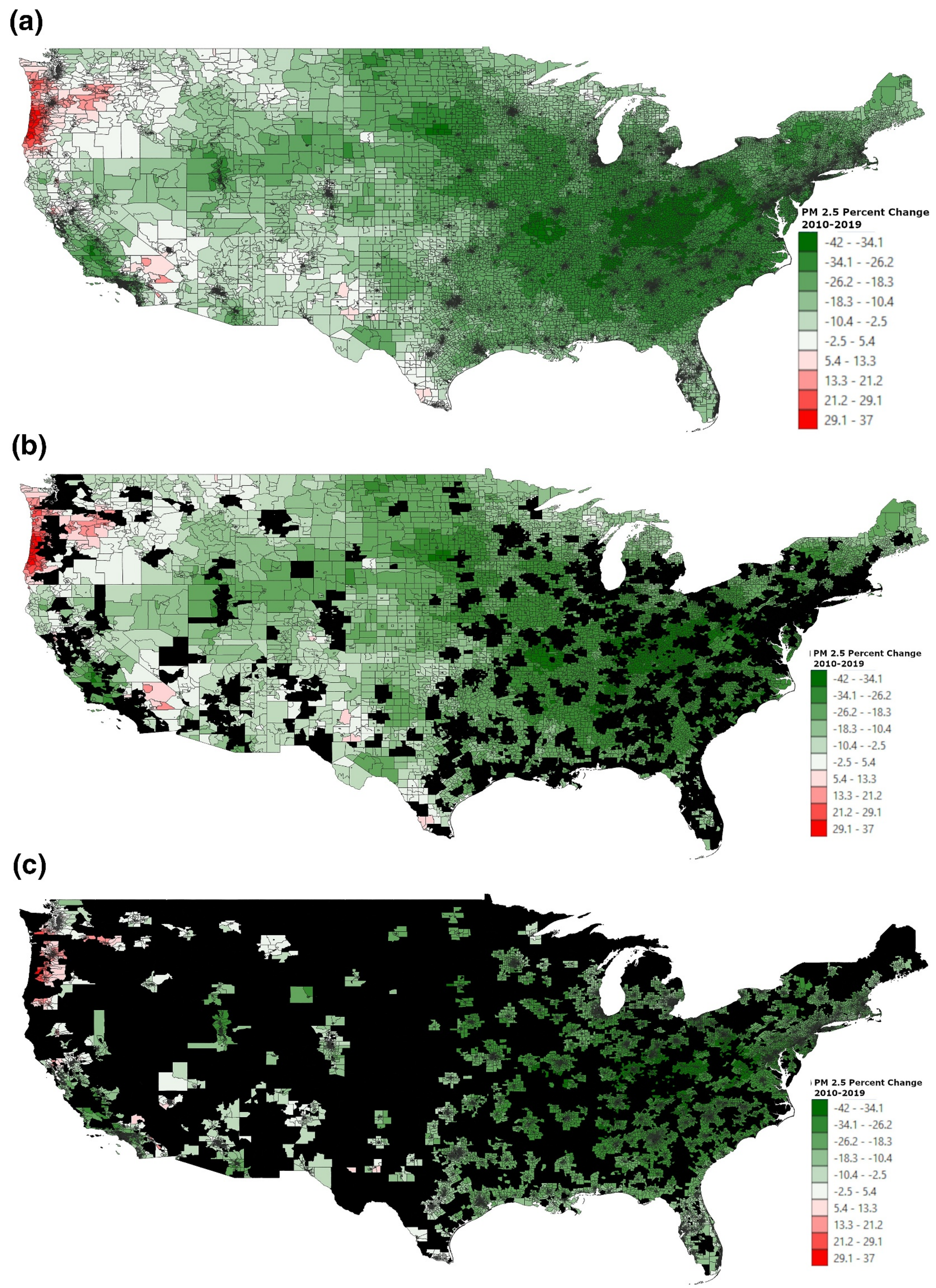

Figure 2. (a) Percent difference of $PM_{2.5}$ concentrations in United States Census Tracts, 2010–2019. (b) Percent difference of Rural $PM_{2.5}$ concentrations in United States Census Tracts, 2010–2019. Urban tracts are hidden. (c) Percent difference of Urban $PM_{2.5}$ concentrations in United States Census Tracts, 2010–2019. Rural tracts are hidden.

4. Discussion

4.1. Summary

This investigation compared the urban-rural differences in ambient $PM_{2.5}$ levels across the census tracts of the United States between 2010 and 2019. Overall, rural communities in the United States had consistently lower $PM_{2.5}$ levels throughout the period of 2010–2019. Continual declining $PM_{2.5}$ across the United States was observed between 2010 and 2019, more rapidly in rural areas than urban areas. $PM_{2.5}$ levels vary substantially across communities by share of race/ethnicity and poverty level. For example, high Black communities, in both rural and urban census tracts, had significantly higher $PM_{2.5}$ pollution levels. Although the current findings are consistent with global concentrations declining in developed countries, disparities related to air pollution exposure persist along racial and poverty lines.

4.2. Comparisons With Prior Evidence

Our findings on differences in $PM_{2.5}$ concentrations between urban and rural settings were similar to the historical patterns found in the literature (Li et al., 2009; Lin et al., 2018; Liu et al., 2023). International sources were included here due to the lack of urban-rural comparisons of $PM_{2.5}$ found in the United States. Reductions in $PM_{2.5}$ levels between 2010 through 2019 were consistent with other findings and consistent with in-between year variations, particularly from 2016 to 2018 (Clay et al., 2021). Lim et al. (2020) report concentrations of $PM_{2.5}$ between 1998 and 2016 decreased in North America. Additionally, they found an increase in population was correlated with $PM_{2.5}$ concentrations, however developed countries were able to successfully increase economic and national growth while at the same time mitigate $PM_{2.5}$ increases. This was less evident in low- and middle-income countries (LMICs) during this same period. Additionally, the increases between 2016 and 2018 that we observed is consistent with other findings; reasons put forth for these interval increases by Clay et al. (2021) include increases in wildfires, additional economic activity, and reductions in the enforcement of the Clean Air Act.

4.3. Effect of $PM_{2.5}$ on Racial Minority, and Socially Disadvantaged Communities

$PM_{2.5}$ exposure has been shown to disproportionately affect the health of minority and socially disadvantaged communities in both urban and rural contexts (Miranda et al., 2011; Raju et al., 2019). In particular, Raju et al. (2019) observed rural residence was a risk factor for Chronic Obstructive Pulmonary Disease (COPD), as well as poverty and the use of coal for heating, which is a main source of indoor PM exposure. Yang et al. (2021) report that outdoor $PM_{2.5}$ accounted for 19.3% of global COPD disability-adjusted life years (DALYs) in 2017. This was more than the DALYs attributable to indoor PM, however the fact remains that any PM exposure is harmful to respiratory health whether indoor, outdoor, rural, or urban. Additionally, Miranda et al. (2011) found that non-Hispanic Black populations were more likely to reside in communities with the worst air quality. Furthermore, rural areas were traditionally underrepresented within air quality monitoring networks, creating a gap in the information for significant portions of the population (Miranda et al., 2011). However, even in areas where monitoring data are available, racial minorities and socially disadvantaged communities experienced higher air pollution levels (Miranda et al., 2011). In this study, modeled data provided estimates for all census tracts in the contiguous United States where this data was unavailable previously (from a national perspective) and it investigated the associations of these estimates on minority and socially disadvantaged communities. Thus, such air quality disparities have persisted over the years, as our study found the same patterns - communities with the highest poverty rates and highest proportion of Black and Hispanic residents experienced the worst air quality measured by $PM_{2.5}$ concentration. Table 1 indicates the highest concentrations observed in 2019 were in Urban Hispanic communities (with Urban Black communities a close second) and the highest quartile of poverty had higher concentrations as well.

Collins et al. (2022) had similar findings to ours in their investigation of the impact of $PM_{2.5}$ on communities of color. They found higher concentrations of short and long-term exposures among Hispanic and Black populations compared to their White counterparts. It is important to highlight that Metropolitan Hispanic populations were those with the highest $PM_{2.5}$ exposures, both short and long-term, as our investigation revealed the similar results (for annual mean exposures alone). They compared their findings to 28 other environmental justice (EJ) studies in the United States that investigated race/ethnicity disparities in $PM_{2.5}$ exposures and arrived at four conclusions: (a) There were disparities of exposure based on people of color (POC) including Black and Hispanic populations;

(b) While overall $PM_{2.5}$ exposures have decreased across the United States between White people and POC, disparities still exist for $PM_{2.5}$ exposures of POC; (c) Low socioeconomic status was associated with higher $PM_{2.5}$ exposure; and (d) More investigation is warranted for short-term $PM_{2.5}$ exposure disparities as there is a gap in the number of studies that have investigated this. This is true for the present investigation, as annual mean concentrations were used alone. Finally, this review suggests that structural racism and classism have persisted to influence exposure disparities of POC and low socioeconomic status, respectively. Furthermore, more attention should be devoted to Hispanic populations as this population appears to have the highest $PM_{2.5}$ exposures.

4.4. The Differences Between Rural and Urban Communities in Terms of Sources of $PM_{2.5}$

Our findings that rural residents experienced lower $PM_{2.5}$ concentrations and where concentrations decreased faster over time, are encouraging given the higher existing COPD and pulmonary diseases in these communities. However, the sources for urban $PM_{2.5}$ and rural $PM_{2.5}$ can vary. For example, domestic fuel burning has been identified as a significant source of $PM_{2.5}$ exposure (Salvi & Barnes, 2009). Raju et al. (2019) observed the use of coal for heating was a risk factor for COPD (a known source of PM and HAP), while adjusting for smoking status. Thus, $PM_{2.5}$ sources and exposures are likely to differ in urban and rural areas for both indoor and outdoor air pollution, especially where solid fuel combustion from coal and wood are routine activities (Raju et al., 2019).

Zhao et al. (2021) summarize several ways $PM_{2.5}$ exposure can be reduced according to its source. These include reducing fossil fuel combustion from coal burning sources (Thurston et al., 2016), improvements in city planning for construction and transportation to reduce particulates like road dust and ensuring residential areas are not constructed near power plants (Chen et al., 2019; Ruiz-Rudolph et al., 2016), and increasing vegetation coverage in areas with low economic activity (de Keijzer et al., 2017).

Wildfire has been observed as a significant source of $PM_{2.5}$ in the United States, accounting for approximately 25% of primary $PM_{2.5}$ across the nation (O'Dell et al., 2019). Its toxicity has been observed to be significant; Xu et al. (2020) report wildfire $PM_{2.5}$ is more toxic than urban sources of $PM_{2.5}$ due to its relative smaller particle size, chemical makeup, and its typical connection with high temperatures. Recent seasonal trends in $PM_{2.5}$ concentrations have been observed due to wildfire increases in the summertime, particularly in the western United States (O'Dell et al., 2019). Furthermore, Masri et al. (2021) found a disproportionate impact of wildfires in California on the elderly and low-income residents between 2000 and 2020. Additionally, the role of climate change on wildfire and subsequent $PM_{2.5}$ exposures must be considered to protect populations disproportionately burdened by these events who have greater susceptibility for adverse health outcomes. For example, Burke et al. (2021) observed that climate change-induced wildfire smoke has the potential to reach similar levels to the projected increases in temperature-related mortality from climate change. Thus, a greater focus of resources, policies, and public health surveillance is warranted, especially for rural low-income communities and other subpopulations susceptible to the adverse effects of $PM_{2.5}$ and wildfires, for example, the elderly, asthmatics, those with COPD and other cardio-pulmonary comorbidities, etc.

Finally, another reason for greater rural $PM_{2.5}$ decline could be the result of population growth and migration toward urban areas. More investigation is needed to explore this trend and verify the associated or causal factors.

4.5. New Policies and Programs Driving the Declining Trends

The evidence for the disproportionate burden of $PM_{2.5}$ on minority and socially disadvantaged communities in both urban and rural settings warrants greater scrutiny on current air quality guidelines. Additionally, recent efforts to review the national air quality guidelines for $PM_{2.5}$, otherwise known as the National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$, were proposed to be lowered in January 2023 by the EPA and its independent scientific advisors. In January 2024, the EPA approved the reduction of this standard. The previous primary annual average standard for $PM_{2.5}$ set in 2012 was 12.0 μg/m^3 and was lowered to 9.0 μg/m^3. However, what was not specifically addressed with the lowering of the $PM_{2.5}$ standard, was the availability of data for the communities and populations disproportionately affected by $PM_{2.5}$. Enforcement of the new standard is an area that should be closely monitored as well as evaluated to prove $PM_{2.5}$ reductions are being observed and maintained. Additionally, this monitoring and evaluation is needed in areas where susceptible populations to poor air quality reside, however often times this data is not being collected. Alongside the overall attempts to lower the national standard for $PM_{2.5}$, increased coverage of air quality monitors is needed to assess levels where populations are most susceptible to the adverse effects of poor air quality. Once granular and specific air quality data is readily available for such communities, for example, those who identify as EJ communities, both evaluation and subsequent improvements to the standard and other policies can be made to protect members of the public that are more geographically proximate and susceptible, for example, persons with asthma, those with COPD, older persons, etc.

4.6. Strengths and Limitations

A limitation of this study was the overall impact of $PM_{2.5}$ is potentially underestimated in rural areas as it did not assess the added contribution of $PM_{2.5}$ from domestic fuel burning for HAP. The findings from prior research, for example, Hendryx et al. (2010) and Rogalsky et al. (2014) support this. Other air pollutants related to HAP beyond $PM_{2.5}$ and ozone, such as, polycyclic aromatic hydrocarbons, were not assessed. Additionally, agricultural sources, for example, ammonia (NH3) from livestock waste and fertilized fields, were also not assessed. Further investigation to quantify the above sources (among others) with similar urban-rural comparisons to acquire state-level estimates is needed for future research. Furthermore, given the urban-rural variability of states, a national comparison of air pollution outside of $PM_{2.5}$ and ozone may not be relevant as inter-state pollution sources can be comparatively complex. Regional investigations or investigations using other shared ecology, land use practices, topography, etc. should be explored in addition to state comparisons. In addition to the underestimates from potential sources of HAP in rural settings mentioned above, another limitation is the $PM_{2.5}$ estimates that were used are likely more uncertain in rural areas than urban areas. Ground truthing modeled estimates of $PM_{2.5}$ concentrations in rural settings can be more resource intensive as air quality monitors are likely near population centers, however this has been evolving recently as more low-cost sensors become more widely available (deSouza & Kinney, 2021). Finally, short term exposures were not investigated in this study, which can have potentially more acute health impacts (i.e., heart attacks and asthma exacerbations), a specificity often beyond what annual concentration assessments can identify (Collins et al., 2022).

The strengths of this investigation were related to its data comparisons using both spatial and temporal factors. The investigation assessed census tract estimates of $PM_{2.5}$ and ozone across the United States between 2010 and 2019 and investigated urban and rural differences in the pollution estimates themselves, as well as socio-demographic characteristics. To our knowledge, no other studies or investigations have compared urban and rural differences across the United States at this level of geographic granularity (census tracts), over this period, for these air pollution estimates and socio-demographic characteristics. $PM_{2.5}$ and ozone are relevant for both urban and rural contexts (given their wide array of sources) and have the most salient public health impacts. This investigation and its findings are significant given the availability and salience of the data using these spatial and temporal factors.

5. Conclusion

This decade-long national study uncovered persistent geographic variations in $PM_{2.5}$ concentrations across the years assessed. Rural areas had lower $PM_{2.5}$ concentrations compared to urban areas, and rural areas showed a more rapid decline of $PM_{2.5}$ concentrations between 2010 and 2019. On top of these differences, $PM_{2.5}$ concentrations varied among communities by race-ethnicity and poverty levels. Efforts should be made for public health and environmental health programs in both urban and rural settings to provide greater protections for minority and socially disadvantaged communities. One of the primary means for greater protection would be to address the availability of air quality monitors, data, and information for populations who are most susceptible to the adverse health impacts of poor air quality.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The $PM_{2.5}$ and population-based data used for the respective air pollution and demographic variables in the study were accessed from the AHRQ SDOH repository (Agency for Healthcare Research and Quality, Rockville, MD, 2023). Data be accessed via the following url: https://www.ahrq.gov/sdoh/data-analytics/sdoh-data.html. The open-source software used for data analyses to generate the quantitative statistical findings included "R" (*R*-

4.3.1 for Windows, n.d.) and "QGIS" for Geographic Information System (GIS) processing (*QGIS A Free and Open Source GIS*, n.d.). They can be found at the following respective urls: https://cran.r-project.org/bin/windows/base/old/ and https://download.osgeo.org/qgis/win64/QGIS-OSGeo4W-3.24.0-1.msi, respectively. Data generated during the analysis and those contained in Figures 1 and 2a–2c, Table 1, and all Supporting Information can be found at the following repository: https://doi.org/10.17605/OSF.IO/GFQ37 (Kilpatrick, 2024).

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