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# Fine particulate matter composition in American Indian vs. Non-American Indian communities

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## Abstract

**Background:** Fine particulate matter ($PM_{2.5}$) exposure is a known risk factor for numerous adverse health outcomes, with varying estimates of component-specific effects. Populations with compromised health conditions such as diabetes can be more sensitive to the health impacts of air

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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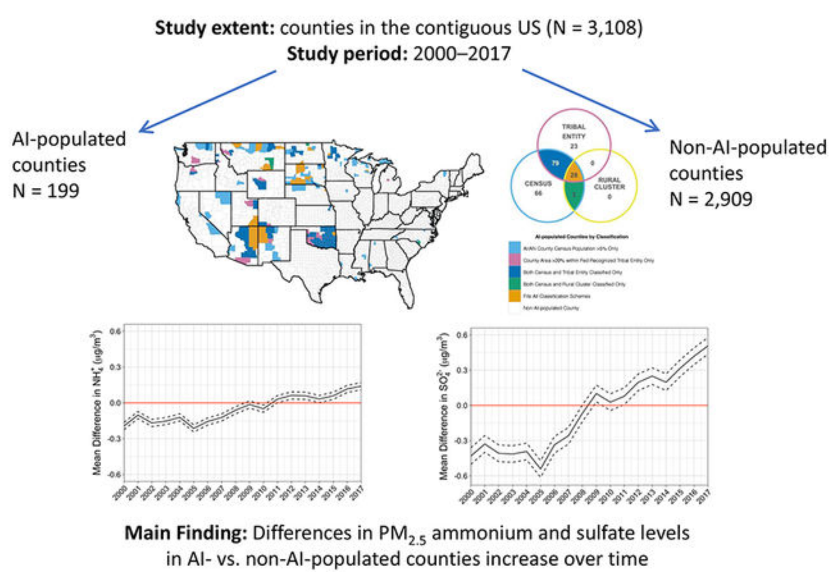
pollution exposure. Recent trends in $PM_{2.5}$ in primarily American Indian- (AI-) populated areas examined in previous work declined more gradually compared to the declines observed in the rest of the US. To further investigate components contributing to these findings, we compared trends in concentrations of six $PM_{2.5}$ components in AI- vs. non-AI-populated counties over time (2000 – 2017) in the contiguous US.

**Methods:** We implemented component-specific linear mixed models to estimate differences in annual county-level concentrations of sulfate, nitrate, ammonium, organic matter, black carbon, and mineral dust from well-validated surface $PM_{2.5}$ models in AI- vs. non-AI-populated counties, using a multi-criteria approach to classify counties as AI- or non-AI-populated. Models adjusted for population density and median household income. We included interaction terms with calendar year to estimate whether concentration differences in AI- vs. non-AI-populated counties varied over time.

**Results:** Our final analysis included 3,108 counties, with 199 (6.4%) classified as AI-populated. On average across the study period, adjusted concentrations of all six $PM_{2.5}$ components in AI-populated counties were significantly lower than in non-AI-populated counties. However, component-specific levels in AI- vs. non-AI-populated counties varied over time: sulfate and ammonium levels were significantly lower in AI- vs. non-AI-populated counties before 2011 but higher after 2011 and nitrate levels were consistently lower in AI-populated counties.

**Conclusions:** This study indicates time trend differences of specific components by AI-populated county type. Notably, decreases in sulfate and ammonium may contribute to steeper declines in total $PM_{2.5}$ in non-AI vs. AI-populated counties. These findings provide potential directives for additional monitoring and regulations of key emissions sources impacting tribal lands.

## Graphical Abstract




### Keywords

air pollution; American Indian; environmental health; environmental justice

## Introduction

Fine particulate matter ($PM_{2.5}$) air pollution is a risk factor for numerous adverse health outcomes, including but not limited to respiratory and cardiovascular diseases (Hystad et al., 2020; Pope et al., 2019; Virani et al., 2020). Racial and ethnic minorities often bear disproportionate burdens of $PM_{2.5}$ exposure and associated morbidity and mortality risk (Bullard, 1993; Jbaily et al., 2022; Tessum et al., 2019). Given extensive environmental degradation on and near tribal lands across the United States (US) (Fernández-Llamazares et al., 2020; Lewis et al., 2017), air pollution is a critical public health concern in many American Indian and Alaska Native (AI/AN) communities (Shriver and Webb, 2009; Woo et al., 2020). AI/AN face a high prevalence of chronic diseases such as diabetes mellitus and these populations may be more susceptible to the health effects of continued air pollution exposure (Centers for Disease Control and Prevention, 2020). Many American Indian (AI) communities are located in the rural US, where $PM_{2.5}$ concentrations have not been well characterized (Dewees and Marks, 2017), as the Environmental Protection Agency (EPA) $PM_{2.5}$ monitors tend to be stationed in more densely populated regions. Moreover, AI communities have historically been excluded from most air pollution epidemiological studies, and our understanding of the human health hazards in these populations is limited.

Our prior work comparing total $PM_{2.5}$ mass concentrations between AI- and non-AI-populated counties across the contiguous US found a lower percent decline over time in $PM_{2.5}$ in AI-populated counties and higher levels in recent years compared to other counties (Li et al., 2022). $PM_{2.5}$ consists of a complex mixture of particles, which vary geographically and temporally and arise from different emission sources (Seinfeld and Pandis, 2016). Comparing levels of $PM_{2.5}$ components could help elucidate the contributions of specific air pollutants and potential sources to total $PM_{2.5}$ trends. This present study considers the six major $PM_{2.5}$ components contributing to total $PM_{2.5}$ mass: ammonium ($NH_4^+$), sulfate ($SO_4^{2-}$), nitrate ($NO_3^-$), black carbon (BC), organic matter (OM), and mineral dust. $NH_4^+$ primarily originates from fertilizer use and livestock production (Dentener and Crutzen, 1994; Schiferl et al., 2014). $SO_4^{2-}$ and $NO_3^-$ are secondary pollutants resulting from the oxidation of sulfur dioxide and nitrous oxides and mainly originate from anthropogenic fossil fuel combustion, wildfires, and volcanoes (Park, 2004). BC and OM can originate from any combustion process but mainly from biomass burning and transportation emissions, and oxidation of OM compounds can further lead to the formation of secondary organic pollutants (Briggs and Long, 2016; Lin et al., 2010). Mineral dust consists of a mixture of aluminum, silicon, calcium, iron, and titanium (van Donkelaar et al., 2019) and arises from wind erosion of particles in deserts, other landscapes (Prospero, 1999) and construction derived dust.

To evaluate trends in compositional $PM_{2.5}$ over time in AI communities, we compared concentrations of $NH_4^+$, $SO_4^{2-}$, $NO_3^-$, BC, OM, and mineral dust from 2000–2017 in the contiguous US between AI- and non-AI-populated counties using predicted estimates from a satellite-based chemical transport model. We hypothesized that trends in specific $PM_{2.5}$ components, namely sulfate, organic matter, and mineral dust, would be differential by AI-populated county type, given the locations of AI-populated counties across the contiguous

US. Furthermore, given varied $PM_{2.5}$ composition by location, we investigated geographic differences in $PM_{2.5}$ component trends by county type through stratifying by rural status and climate region.

## Methods

Our analysis included 3108 study counties, derived from counties and county equivalents across the 48 contiguous US and the District of Columbia. We used a three-criteria scheme to classify study counties with substantial AI populations as "AI-populated counties" as in our prior study (Li et al., 2022). Counties were classified as AI-populated if they fit one or more of the following criteria: (1) reported greater than 5% self-identified population of AI/AN in the 2010 Census ("census" classification), (2) contained at least 20% areal overlap with a federally-recognized tribal entity ("Tribal entity" classification), or (3) were previously classified as a rural AI county in a nationwide analysis using k-means clustering ("rural cluster" classification) (Wallace et al., 2019). We included counties that did not meet these criteria as "non-AI-populated" in our analysis. In earlier work, we described the breakdown of AI-populated counties by the three classification schemes in more detail (Li et al., 2022).

We compared airborne concentrations of $SO_4^{2-}$, $NH_4^+$, $NO_3^-$, BC, OM, and mineral dust from 2000–2017 in counties defined as AI- vs. non-AI-populated. We conducted our analysis at the county level to provide findings relevant for informing regulatory policymaking.

### Annual $PM_{2.5}$ Component Concentrations

We extracted airborne concentrations of particle-phase $NH_4^+$, $SO_4^{2-}$, $NO_3^-$, BC, OM, and mineral dust from satellite-based surface $PM_{2.5}$ models that provide annual predictions of each $PM_{2.5}$ component at approximately 1 $km^2$ grid resolution across the US (van Donkelaar et al., 2019). These models incorporated satellite retrievals, chemical transport modeling (GEOS-Chem), and ground-based measurements to derive total $PM_{2.5}$ mass, which were then partitioned into $PM_{2.5}$ compositional species using a GEOS-Chem chemical transport model simulation. Next, these $PM_{2.5}$ component estimates were statistically fused with ground monitor data to yield accurate continuous surfaces despite sparse compositional monitor density in many regions of the US. These models exhibit relatively high predictive accuracies. Cross-validated $R^2$ values for the six $PM_{2.5}$ components range from 0.57 to 0.96 with the strongest for $SO_4^{2-}$ ($R^2$ = 0.96) and $NO_3^-$ ($R^2$ = 0.90) and the lowest for OM ($R^2$ = 0.57).

We estimated modeled annual concentrations of the six components separately for every study county by averaging the $PM_{2.5}$ component concentrations in all grids with their centers contained in each study county.

### Covariates

We included county-level population density and median household income from the 2010 Census to examine differences in $PM_{2.5}$ component concentrations between AI-populated and non-AI populated counties independent of these factors. Given that population density and income distributions are highly skewed across US counties, we included deciles of their distributions as categorical variables in the regression models.

### Statistical Analysis

We ran separate linear mixed regression models to compare annual concentrations of the six $PM_{2.5}$ components in AI- versus non-AI-populated counties. The primary analysis included six regression models for each component separately, with $NH_4^+$, $SO_4^{2-}$, $NO_3^-$, BC, OM, or mineral dust concentrations as the response variable in each model. The predictor variable of interest in our statistical models was binary AI-populated county type. We accounted for potential within-state correlation using random intercepts for each state and for correlation of observations over time in counties using nested random intercepts for counties within states. We adjusted each regression model for calendar year (categorical), population density (deciles), and median household income (deciles). To evaluate whether the trends in $PM_{2.5}$ components varied over time between AI- vs. non-AI-populated counties, we included interaction terms between county type and each calendar year in the above models. Specifically, we ran one set of models including main effects only and another set additionally including county type and year interaction terms. To assess the presence of statistically significant modification of the AI-populated county-type effect measure over time, we compared the two sets of models using likelihood ratio tests.

We used R Statistical Software, version 3.6.3, to conduct all statistical analyses. The code and datasets used to run the present analyses are publicly available and accessible at: https://github.com/maggie-mengyuan-li/pm2.5_comp_ai.git.

### Secondary analysis

We ran a secondary analysis stratifying by rural and non-rural counties using the 2013 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties (Rothwell et al., 2014). Rural counties comprised of nonmetropolitan (i.e., micropolitan and noncore) counties defined by the NCHS and non-rural counties included metropolitan counties. Since the relative composition of $PM_{2.5}$ widely differs by climate and geography over time (Seinfeld and Pandis, 2016), we conducted a secondary analysis of the models containing county type and year interaction terms stratifying by grouped US climate regions as defined by the National Oceanic and Atmospheric Administration (NOAA), using the following categorizations: West/Northwest (combining the West and Northwest climate regions due to low count of AI-populated counties), Northern Rockies and Plains, Southwest, Upper Midwest, South, and East (combining the Ohio Valley, Northeast and Southeast climate regions).

### Sensitivity Analyses

We ran a sensitivity analysis additionally adjusting for US climate regions. To account for spatial autocorrelation of $PM_{2.5}$ component concentrations across counties, we also ran sensitivity analyses using geoadditive modeling with an additional tensor-product smooth term for latitude and longitude of the county centroid. For our geoadditive models, we considered 10 knots as our default for the six components. We examined a varying number of knots (5, 10, and 20) for two components, $NH_4^+$ (a relatively spatially homogenous component) and BC (a relatively spatially heterogeneous component).

## Results

Of the 3108 counties included in our analysis, we classified 6.4% (n = 199) as AI-populated and 93.6% (n = 2909) as non-AI-populated. Between 2000 and 2017, the mean concentrations for total $PM_{2.5}$, $NH_4^+$, $SO_4^{2-}$, $NO_3^-$, BC, and OM were lower in AI-populated counties than non-AI-populated counties, while the mean concentration of mineral dust across the study period was higher in AI-populated counties (Table 1). The distribution of population density and household income by AI- vs. non-AI-populated counties are detailed further in Table 1.

Across the contiguous US, county-level concentrations of $NH_4^+$, $SO_4^{2-}$, and $NO_3^-$, BC, and mineral dust declined between 2000–2017 (Figure 1, bolded dashed lines). Adjusted concentrations of all components were slightly but significantly lower in AI-populated counties on average across the study period (Table 2). Using likelihood ratio tests, we detected statistically significant variation in AI-populated county type estimates over time for all six $PM_{2.5}$ components.

On average, between 2000 and 2017, $NH_4^+$ was 0.05 μg/m$^3$ (95% confidence interval [CI]: 0.03, 0.07) lower and $SO_4^{2-}$ was 0.06 μg/m$^3$ (95% CI: 0.02, 0.10) lower in AI-populated counties compared to non-AI-populated counties (Table 2). Although $NH_4^+$ and $SO_4^{2-}$ concentrations were lower at baseline in AI- vs. non-AI-populated counties, this difference was attenuated over time through 2010. After around 2011, concentrations were higher in AI-populated counties compared to the other study counties for both $NH_4^+$ and $SO_4^{2-}$ (Figure 2A-B). Using estimated values from the mixed models with interaction terms, we predicted that from 2000 through 2017, $NH_4^+$ concentrations decreased by 64.7% in AI-populated counties and by 85.3% in non-AI-populated counties (Figure 1A, bolded solid lines). $SO_4^{2-}$ concentrations decreased by 39.8% in AI-populated counties and 69.7% in non-AI-populated counties (Figure 1B, bolded solid lines).

Across the study period, $NO_3^-$ was on average 0.12 μg/m$^3$ (95% CI: 0.08, 0.16) lower in AI- compared to non-AI-populated counties (Table 2). Although we detected statistical effect modification over time and consistently lower levels in AI-populated counties across the study period, the maximal difference in $NO_3^-$ in any given year between AI- and non-AI-populated counties was similar in magnitude to $NH_4^+$ and smaller in magnitude than for $SO_4^{2-}$ (Figure 2C). When we compared component concentrations using estimated values from our primary linear mixed models, $NO_3^-$ concentrations between 2000 and 2017 decreased by 36.8% for AI-populated counties and 43.1% for non-AI-populated counties (Figure 1C, bolded solid lines).

Concentrations of BC were also lower in AI-populated vs. non-AI-populated counties on average between 2000 and 2017 (Table 2). Although we detected statistically significant effect modification of differences by county type over time, there was no clear pattern in this difference from year to year (Figure 2D). We estimated that BC concentrations decreased by 0.36% in AI-populated counties and by 15.3% in non-AI-populated counties over time (Figure 1D, bolded solid lines).

Between 2000 and 2017, OM and mineral dust concentrations were lower in AI-populated vs. non-AI-populated counties (Table 2). Despite statistically significant changes over time by county type for both components, we did not observe any consistent patterning in changes of this difference across the study period (Figure 2E-F). Estimated concentrations over time reflected a 12.5% increase in OM in AI-populated counties and 2.2% decrease in non-AI-populated counties. There was a 19.3% decrease in mineral dust in AI-populated counties and 17.4% decrease in non-AI-populated counties (Figure 1E-F, bolded solid lines).

Comparing rural to non-rural counties, the relative contributions of $SO_4^{2-}$ to total $PM_{2.5}$ were generally higher in non-rural counties, whereas relative contributions of mineral dust to total $PM_{2.5}$ were generally higher in rural counties (Supplementary Table S1). The median relative contributions of ammonium, nitrate, BC, and OM to total $PM_{2.5}$ differed by less than 1% between rural and non-rural counties. The overall differences in component levels estimated across the study period between AI- and non-AI-populated counties were similar in magnitude and direction in rural counties compared to the primary analysis; in non-rural counties, the estimates also did not differ substantially from the primary analysis, with wider confidence intervals observed (Table 2). Annual estimated differences over time in mean concentrations for all six components in AI-populated vs. non-AI-populated counties were similarly patterned across rural and non-rural counties to our primary analysis (Supplementary Figure S4-5).

Evaluating county type differences over time across climate regions, the number of AI-populated counties in each stratum varied from 11 in the East (Ohio Valley, Northeast, and Southeast climate regions) to 72 in the South climate region (Supplementary Figures S2-7). In the West/Northwest, Northern Rockies and Plains, and East climate regions, there were no substantial changes in component level differences over time by AI-populated county type (Supplementary Figures S2, S3, S7). In the Southwest and Upper Midwest climate regions, concentrations of $NH_4^+$, $SO_4^{2-}$, and $NO_3^-$ were generally lower in AI-populated counties across all study years, but this difference was attenuated over time (Supplementary Figures S4-5). In the South climate region, $SO_4^{2-}$ and OM concentrations became somewhat higher after 2008 in AI-populated counties, while concentrations of $NH_4^+$ were higher during the middle of the study period (2008–2012) in AI-populated counties (Supplementary Figure S6).”

### Sensitivity Analysis

When we additionally adjusted for climate region, average differences across the study period and over time did not vary considerably from our primary analysis (Table 2 and Supplementary Figure S6). In our geoadditive models, which included a tensor product between latitude and longitude to account for spatial autocorrelation in component concentrations, findings for all components were also consistent with our primary analysis (Table 2 and Supplementary Figure S7). Estimates did not substantively differ when we used 5, 10, and 20 knots (results not shown).

## Discussion

We analyzed differences in six $PM_{2.5}$ component concentrations from 2000 through 2017 between AI- and non-AI-populated counties across the contiguous US. For most components, levels were lower on average in AI-populated counties vs. non-AI-populated counties. When examining differences in annual concentrations over time, we detected increasing trends in AI- vs. non-AI-populated county type for $NH_4^+$ and $SO_4^{2-}$. For BC, OM, and mineral dust there were no clear differences over time by county type; For $NO_3^-$, the differences between AI- vs. non-AI-populated counties were small; yet consistently lower for AI- vs non-AI-populated counties over the entire study period. Overall, the percent declines over time were higher in levels of $NH_4^+$, $SO^{42-}$, $NO_3^-$, and BC in non-AI- vs. AI-populated counties, while for OM and mineral dust they were higher in AI- vs. non-AI-populated counties.

Furthermore, based on results from the climate region-stratified analyses, differences in $NH_4^+$ and $SO_4^{2-}$ over time by county type may be somewhat driven by differences in the Upper Midwest and South climate regions. $NH_4^+$ exists as a component of $PM_{2.5}$ in two primary forms: ammonium sulfate and ammonium nitrate. Ammonium sulfate, which includes $SO_4^{2-}$, makes up a substantially higher proportion of total $PM_{2.5}$ in the Midwestern and Eastern US while ammonium nitrate, which includes $NO_3^-$, contributes to a higher proportion of total $PM_{2.5}$ in the Western US. In previously published work, we estimated overall declines in $PM_{2.5}$ with steeper declines in non-AI-populated counties. Our findings suggest that ammonium sulfate differences by county type are likely related to total $PM_{2.5}$ differences by county type in our previous study (Li et al., 2022), given the similarity in the magnitude and direction of time trends of $NH_4^+$, $SO_4^{2-}$, and total $PM_{2.5}$ differences by county type. Ammonium sulfate levels have drastically reduced overall in non-AI-populated counties across the study period, with particularly steeper declines relative to AI-populated counties estimated after 2011. In contrast, there has been little to no decline in many AI-populated counties. Common sources of ammonium sulfate include sulfur dioxide emissions from coal-fired power plants and steel production, and ammonia from agriculture (Speight, 2017). Mass closures of coal-fired power plants in recent decades in these regions (Midwest and East) could be a factor contributing to differences in $NH_4^+$ and $SO_4^{2-}$ in AI-populated vs. non-AI-populated counties across our study period (Seinfeld and Pandis, 2016).

The existing literature on air pollution in indigenous communities is limited and findings have been mixed. A recent study reported that population-weighted average concentrations of total $PM_{2.5}$ for Native Americans were lower from 2000–2016 compared to Black, White, Hispanic, and Asian communities across ZIP Code Tabulation Areas (ZCTAs) nationwide (Jbaily et al., 2022). Mortality rates in 2014 attributable to $PM_{2.5}$ exposure from electricity generation sources were lower among Native Americans compared to other racial and ethnic groups overall across the US, but higher for Native Americans in Oklahoma, a state containing a substantial proportion of AI-populated counties (Thind et al., 2019). Our study also detected lower concentrations of all six components in AI-populated counties on average from 2000–2017. However, none of the previous studies examined differences in trends over time by an AI- vs non-AI classification for total $PM_{2.5}$ or its components. In our previous study (Li et al., 2022), we also detected overall lower $PM_{2.5}$ concentrations in

AI-populated counties, but a slower rate of decrease in $PM_{2.5}$ concentrations in AI-populated counties over time resulted in higher $PM_{2.5}$ concentrations in more recent years. With this present study, we expand our previous findings and show that the concentrations of specific components, namely $SO_4^{2-}$ and $NH_4^+$, reflect a similar pattern of differences over time by AI-populated county type as total $PM_{2.5}$ concentration.

Stronger adverse health outcomes have been detected for exposure to specific $PM_{2.5}$ components. Studies have found that exposure to $NH_4^+$, $SO_4^{2-}$, and $NO_3^-$ is associated with an increased risk of asthma exacerbation and other respiratory effects (US EPA, 2019). Higher effects were explicitly estimated in regions with high correlations between these components and total $PM_{2.5}$ (US EPA, 2019). One study observed an increase in all-cause mortality risk from exposure to higher levels of $NH_4^+$ and decreased risk from higher levels of $NO_3^-$, across multiple cities in different countries (Masselot et al., 2022). Increased exposure to $SO_4^{2-}$ was associated with a higher risk of cardiopulmonary mortality (Brook et al., 2010), and exposure to sulfur originating from coal combustion was positively correlated with coronary heart disease risk (Thurston et al., 2016). AI/AN populations face significantly higher burdens of cardiovascular disease and diabetes compared to white Americans and other racial and ethnic groups (Hutchinson and Shin, 2014). Existing studies have found that persons with diabetes appear to display proinflammatory responses to short- and long-term exposure to air pollution (Jacobs et al., 2010). Higher levels of air pollution were associated with higher rates of CVD incidence, hospitalizations, and mortality for persons with diabetes (Hart et al., 2015; Pereira Filho et al., 2008; Pinault et al., 2016). Thus, AI/AN populations may be at a higher risk for $PM_{2.5}$- and component-specific CVD-related adverse health outcomes. Substantial barriers to accessing quality healthcare, such as geographic isolation and lack of transportation access, are prevalent in rural AI/AN communities, further exacerbating health burdens (Cromer et al., 2019). Characterizing trends in $PM_{2.5}$ components and identifying those with the largest differences between AI- vs. non-AI-populated counties is critical for maximally efficient policies to protect public health equitably.

## Limitations

First, the ecological design of this study limits our ability to draw conclusions and comparisons at the community or individual levels. Second, uncertainties in the predicted estimates of $PM_{2.5}$ components, if correlated with temporal changes in concentrations, may induce some bias in the estimated effects of AI-populated county type on $PM_{2.5}$ concentrations. Third, due to the scarcity of monitoring data of speciated $PM_{2.5}$ in predominantly rural and American Indian communities, we are unable to compare patterns of ground-level concentrations between AI-populated vs. non-AI-populated counties; since this analysis incorporates modeled predictions of $PM_{2.5}$ component concentrations, potential differences in predicted $PM_{2.5}$ model performance in AI- vs. non-AI-populated counties given fewer monitors in highly rural areas could influence the validity of our findings and conclusions. Future work currently under development to begin to address this present limitation includes planned residential monitoring of $PM_{2.5}$ components in American Indian communities in the Southwest and Great Plains. Fourth, analyzing annual concentrations of $PM_{2.5}$ components cannot capture any seasonal variability in levels of various components, which could fluctuate substantially. Fifth, while broad in scope, our method of classifying AI-populated counties may not capture counties with substantial AI/AN populations. In particular, the census definition in our classification scheme for AI-populated counties incorporated data from the 2010 Census. Data from the 2020 Census showed an 86.5% increase in the self-reported AI/AN population, indicating a historical undercount of AI/AN in previous census reports (ICT, 2021). As of 2022, the majority of AI/AN lived in metropolitan areas (U.S. Department of Health and Human Services Office of Minority Health, 2023). Although we conducted a secondary analysis stratifying by rural status and did not detect substantive differences from our primary analysis findings, our county-level analysis is unable to assess exposure burdens among the large urban AI population and thus cannot generalize exposure patterns among the AI population as a whole. AI-populated counties are not randomly distributed across the US and certain climate regions have no or very few AI-populated counties, limiting the statistical power of the climate region stratified analyses; thus, these results may not be wholly representative in estimating differences between AI-populated vs. non-AI-populated communities regionally. Further research conducted at finer resolutions could potentially investigate differences in concentrations associated with distinct Indigenous cultural regions and environmental regions. There is also potential for residual confounding by socioeconomic status by factors other than household income, population density, or climate region. Finally, we could not compare levels of other components, such as trace metals, that pose substantive risks to human health. Nonetheless, the components we examined are the largest contributors to total $PM_{2.5}$ mass.

## Conclusions and Policy Implications

Air pollution in tribal areas is a widely known issue among many AI communities. Our previous work highlighted slower declines in total $PM_{2.5}$ over time in AI- vs. non-AI-populated counties (Li et al., 2022). The examination of $PM_{2.5}$ component trends revealed that specific components, namely $NH_4^+$ and $SO_4^{2-}$, may be contributing to these slower declines in AI-populated counties. Future work investigating $PM_{2.5}$ emissions in AI-populated counties could elucidate sources of air pollution impacting tribal lands and areas with large populations of AI people. Additional monitoring is also needed to further validate the ground accuracy of analyses using modeled data. The resourcefulness of tribal air programs in data collection and management invites many opportunities for collaboration and mutual learning among researchers, federal and state agencies, and tribal governments. These collaborations could aid in addressing the critical gap in air pollution research to ensure that tribal populations are being considered when informing the National Ambient Air Quality Standards. The establishment of stable funding mechanisms and institutional infrastructure can continue to improve tribal air pollution monitoring and regulatory efforts.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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- $PM_{2.5}$ components levels on average were lower in AI-vs. non-AI-populated counties
- $NH_4^+$ and $SO_4^{2-}$ levels lower at baseline, higher over time in AI-populated counties
- $NO_3^-$ levels lower throughout study period in AI-populated counties
- Ammonium sulfate reflect similar trends to total $PM_{2.5}$ by AI-populated county type

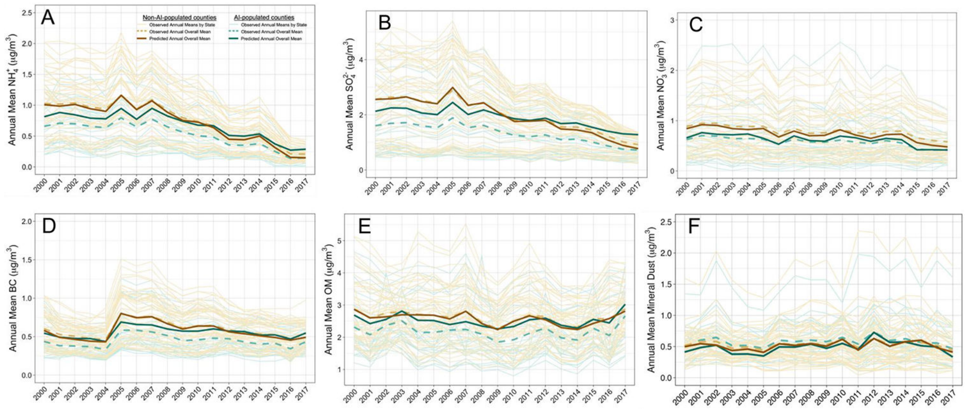


**Figure 1:**

Trends in observed and predicted concentrations of six $PM_{2.5}$ components over the study period (2000 – 2017) for AI and non-AI populated counties. The thin, light-colored teal and brown lines display the observed (raw data) state-specific annual means for AI- and non-AI-populated counties. The bolded dashed teal and brown lines show the observed annual concentrations averaged across all 48 states for AI- and non-AI-populated counties. The bolded solid teal and brown lines indicate the estimated annual concentrations from our linear mixed regression model with county type × year interaction terms, averaged across states for AI- and non-AI populated counties, for decile groups of median annual household income between $40,300 and $42,400 and population density between 22 and 33 individuals per sq mile.

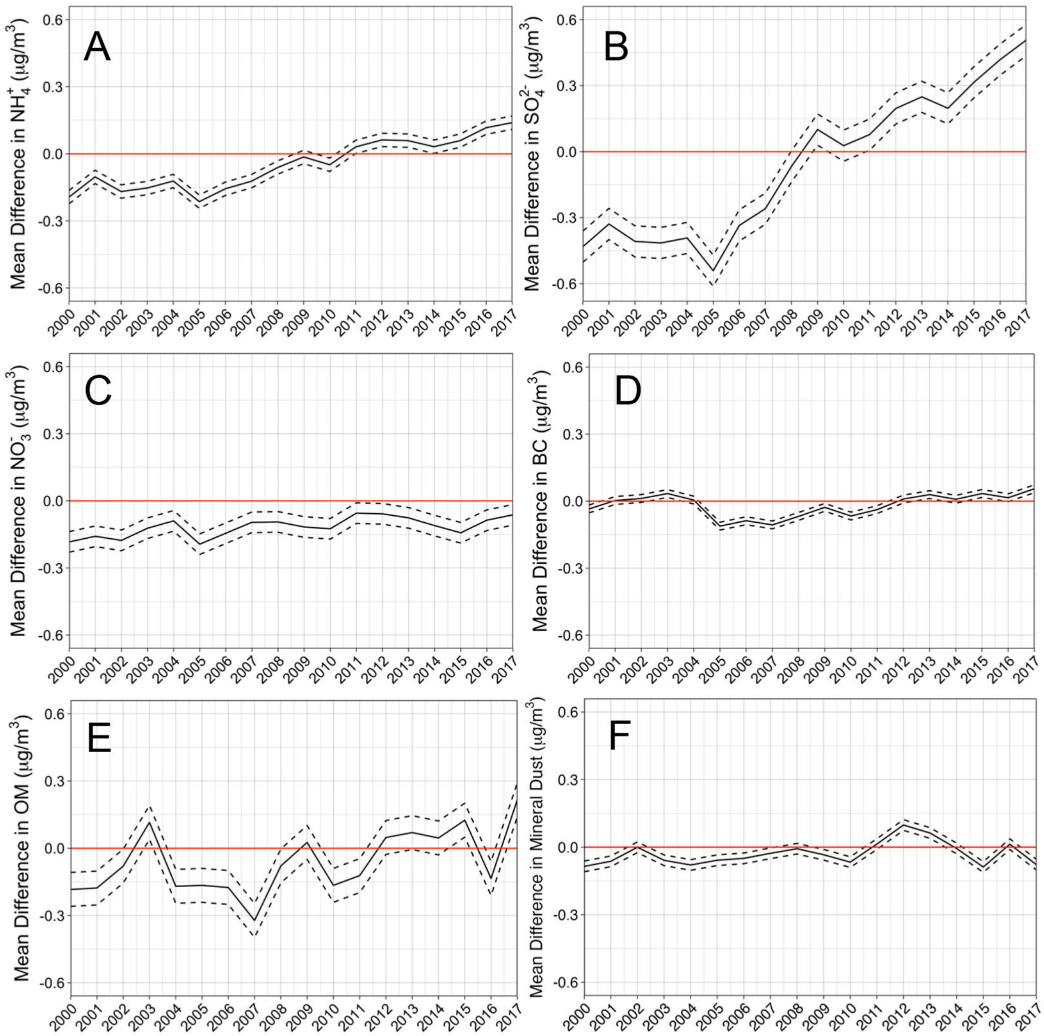


**Figure 2: Mean difference in annual $PM_{2.5}$ component concentrations between AI- and non-AI-populated counties: 2000–2017.**

The solid line represents the total estimated effect (adjusted for calendar year, random intercepts for counties within states, population density and income deciles, and county type × year interaction) of being classified as an AI-populated county vs. non-AI-populated county on annual concentrations of each $PM_{2.5}$ component over the study period; the dashed lines show the 95% confidence intervals from the primary analysis. The solid red line represents no difference on average in adjusted component concentrations between AI and non-AI-populated counties.

**Table 1:**

Descriptive Statistics for AI- and Non-AI-Populated Counties: United States; unadjusted averages across 2000–2017.

| Characteristic | County Type | |
|---|---|---|
| | **AI** | **Non-AI** |
| Number of counties (n) | 199 | 2909 |
| | ***Mean (SD)*** | |
| AI population (%) | 18.2 (19.9) | 0.6 (0.6) |
| Total $PM_{2.5}$ (μg/m$^3$) | 6.3 (2.1) | 8.4 (2.2) |
| $NH_4^+$ (μg/m$^3$) | 0.56 (0.34) | 0.80 (0.46) |
| $SO_4^{2-}$ (μg/m$^3$) | 1.4 (0.83) | 2.2 (1.15) |
| $NO_3^-$ (μg/m$^3$) | 0.66 (0.42) | 0.86 (0.58) |
| BC (μg/m$^3$) | 0.46 (0.18) | 0.63 (0.25) |
| OM (μg/m$^3$) | 2.2 (0.82) | 2.8 (0.92) |
| Mineral Dust (μg/m$^3$) | 0.66 (0.34) | 0.57 (0.27) |
| Population Density (per mi$^2$) | 41 (116) | 276 (1790) |
| Median Annual Household Income (×$1,000) | 40.4 (7.6) | 44.4 (11.6) |

**Table 2:**

Mean (95% CI) difference in modeled $PM_{2.5}$ component concentrations (μg/$m^3$), comparing AI populated vs. non-AI-populated counties (2000 – 2017).

| | Primary analysis[a] | Adjusted for climate region[b] | Adjusted for latitude/longitude[c] | Stratified by Rural Status[d] (Secondary Analysis) | |
|---|---|---|---|---|---|
| | | | | Rural | Non-rural |
| $NH_4^+$ | −0.05 (−0.07, −0.03) | −0.05 (−0.07, −0.03) | −0.01 (−0.02, 0.00) | −0.04 (−0.06, −0.02) | −0.04 (−0.10, 0.02) |
| $SO_4^{2-}$ | −0.06 (−0.10, −0.02) | −0.06 (−0.10, −0.02) | −0.06 (−0.10, −0.02) | −0.06 (−0.10, −0.01) | −0.07 (−0.19, 0.05) |
| $NO_3^-$ | −0.12 (−0.16, −0.08) | −0.11 (−0.16, −0.07) | −0.03 (−0.05, −0.00) | −0.09 (−0.13, −0.05) | −0.08 (−0.19, 0.03) |
| BC | −0.02 (−0.03, −0.01) | −0.02 (−0.03, −0.01) | −0.01 (−0.02, 0.00) | −0.02 (−0.03, −0.00) | −0.01 (−0.05, 0.03) |
| OM | −0.06 (−0.12, −0.01) | −0.06 (−0.12, −0.00) | −0.03 (−0.08, 0.01) | −0.04 (−0.10, 0.01) | −0.09 (−0.26, 0.08) |
| Dust | −0.03 (−0.05, −0.01) | −0.03 (−0.05, −0.01) | −0.01 (−0.02, −0.00) | −0.01 (−0.03, 0.00) | −0.01 (−0.03, −0.00) |

[a] Model adjusted for calendar year, population density and income deciles, and random intercepts for counties within states

[b] Model additionally adjusted for NOAA climate region

[c] Geoadditive model with a tensor term for latitude and longitude

[d] Separate analyses for micropolitan and noncore counties (Rural) and metropolitan counties (Non-rural) defined by the CDC NCHS