The use of Race and Ethnicity in Air Pollution Epidemiology literature in California

Final Report

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Abstract

Air pollution remains a significant global health risk and exposure to air pollutants can lead to multiple health issues across the life course. Furthermore, air pollution plays a crucial role in health disparities across racial and ethnic (RE) groups, through both differential exposure and differential susceptibility. The concept of environmental justice encompasses fair treatment in environmental policies across all race/ethnic groups, cultures, and incomes. Historical patterns of discriminatory siting of emission sources have led to differential exposure to air pollution among racial and ethnic groups. Additionally, differential susceptibility, influenced by social factors and community composition, further exacerbates health inequities. Various conceptual frameworks explain the root causes of these disparities, including economic factors, sociopolitical dynamics, and historical discrimination. Structural racism manifests in multiple ways, affecting psychosocial stress, built environment quality, and healthcare access.

In this report, we aimed to summarize the use of RE in air pollution epidemiology literature in California and make methodological recommendations. We first conducted a scoping review to understand the landscape on the use of RE in air pollution-related health studies in California. From 2000 to 2023, we identified a total of 134 publications. Studies exploring air pollution disparity across RE or RE as effect modifiers for air pollution-outcome relationship increased over time, but the number of publications exploring the mediating role of air pollution in outcome disparity across RE remained low. We summarized methodological challenges in such studies and provided corresponding recommendations.

Introduction

Background of environmental justice and air pollution

According to the Global Burden of Disease study, air pollution was ranked the fourth largest risk factor contributing to premature death globally in 2019, accounting for 6.7 million premature deaths (Murray et al. 2020). Inhalation of air pollutants can lead to inflammatory responses that promote systemic oxidative stress, activation of lung autonomic nervous system, and thrombosis coagulation (Chin 2015; Stanek et al. 2011). Exposure to air pollution has been linked with increases in risk for all-cause, cardiovascular and respiratory mortality and morbidity by many epidemiological studies (Chen and Hoek 2020; Huangfu and Atkinson 2020; Kulick et al. 2023; Lee et al. 2020; Orellano et al. 2020, 2021; Zheng et al. 2021). Aside from abundant epidemiological evidence on detrimental health impacts of air pollution, evidence also supports the important role of environmental determinants like air pollution on health disparities across racial and ethnic groups, potentially through differential exposure and differential susceptibility (Heo et al. 2019; Hicken et al. 2023; Mohai et al. 2009). As a result, the public and government agencies in the United States increasingly emphasized the consideration of environmental justice in policymaking to mitigate health inequities (House 2021; U.S. EPA and WHO partner to protect public health; US EPA 2015). However, the majority of air pollution-related health studies, as well as the broader environmental health sciences field, have been criticized for having a pervasive racism, lacking appropriate consideration of racial and ethnic inequities (Payne et al. 2021; Perry et al. 2021).

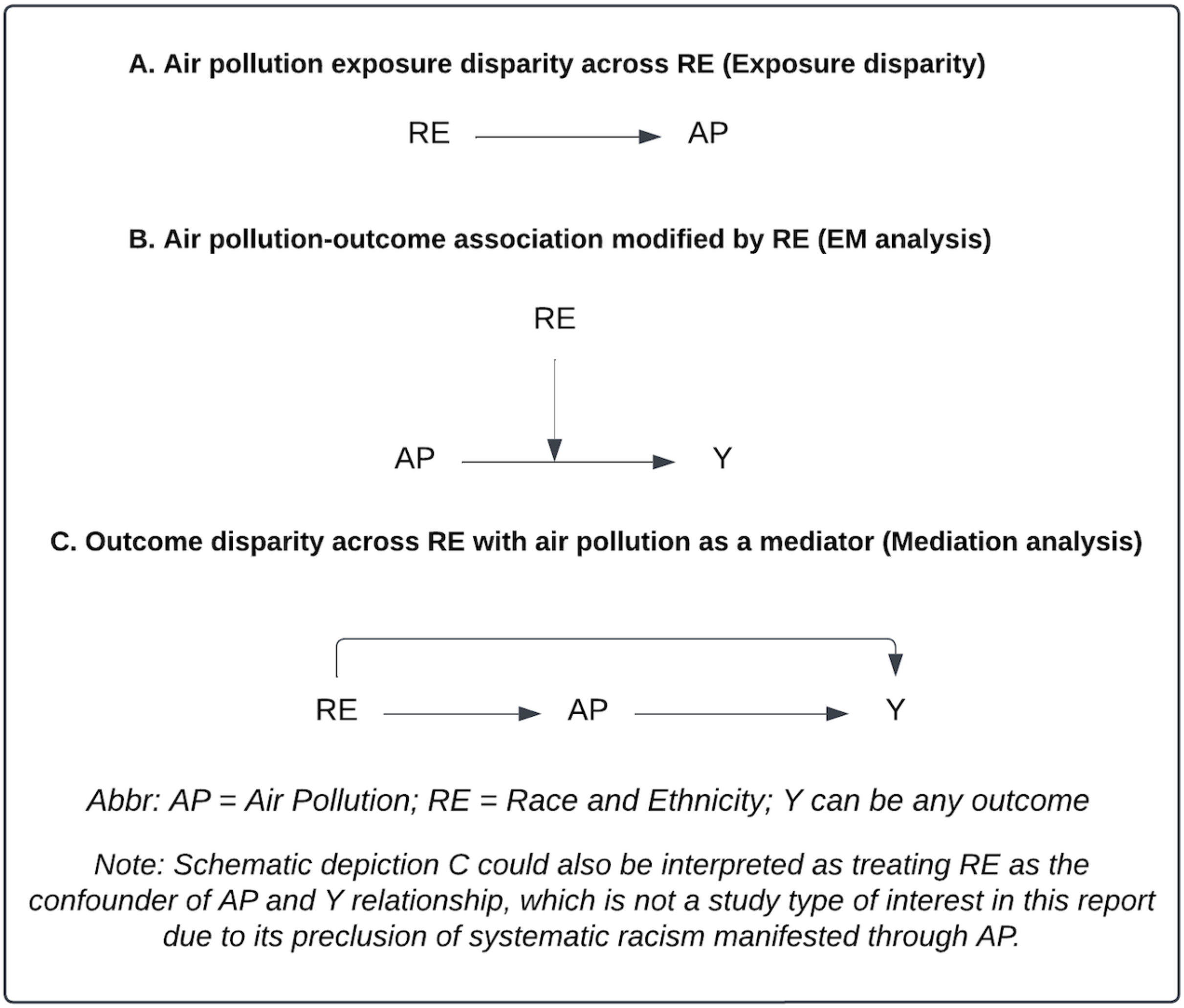
The State of California defined "environmental justice" as "the fair treatment of people of all races, cultures, and incomes with respect to the development, adoption, implementation, and enforcement of environmental laws, regulations, and policies" (Environmental Justice 2011). However, health inequities across racial and ethnic groups have been recognized and recorded in the US since the founding of colonial America (Bailey et al. 2017). The role of environmental determinants, like air pollution, in such health inequities received more attention since the Warren County landfill protest in 1982, when civil rights activists organized against the dumping of polychlorinated biphenyls in the predominantly Black community in North Carolina (Mohai et al. 2009). Since then, many studies have documented the differential distribution of environmental pollutants like air pollution across racial and ethnic groups (i.e., differential exposure), as a result of discriminative sitings of emission sources (Jbaily et al. 2022; Liu et al. 2021; Mohai et al. 2009). Furthermore, environmental determinants like air pollution could also impact health inequities through differential susceptibility, meaning the effect of toxicants on biological systems is modified by social factors like individual race and ethnicity (RE), as well as racial and ethnic composition of the community (details on mechanisms below) (Gee and Payne-Sturges 2004; Jackson and VanderWeele 2019). Being a member of racial and ethnic minority groups or residing in communities mostly composed of minorities not only leads to higher environmental pollutants but also increases the health responses towards such pollutants. Previous studies have demonstrated that disregarding either aspect will lead to an underestimation of the health disparity (Spiller et al. 2021).

Different conceptual frameworks exist in explaining the root causes of the differential exposure and differential susceptibility. Theories for siting patterns leading to differential exposure include lower cost to industrial facilities near minority communities (i.e., economic explanation), less effective opposition from minority communities due to lack of pre-existing social capital (i.e., sociopolitical explanation), and discriminatory zoning in the early 1900s (i.e., side-effect of discrimination from historical policies) (Mohai et al. 2009). On the other hand, historical and structural racism should be considered as a plausible explanation of observed differential susceptibility across both individual and community-level RE (Payne et al. 2021). The structural racism can be manifested in psychosocial stress, quality of built environment, internal dose, and health care quality and access (Bailey et al. 2017; Gee and Payne-Sturges 2004; Morello-Frosch and Lopez 2006). Importantly, individual RE, commonly misconstrued as a fixed biological trait that solely determines the disparity in health responses to environmental pollutants (i.e., biological determinism), should be considered as a social and political construct that leads to differential access to the goods, services, and opportunities of society by RE (Jones 2000; Payne et al. 2021).

Framework to summarize the use of RE in air pollution epidemiology

In this report, we used the operationalization of RE in environmental epidemiology summarized by Benmarhnia et al. to discuss the related assumptions and challenges in these analytical decisions, and to connect these analytical decisions to the above conceptual frameworks. Briefly, in an air pollution-related health study, RE has been used as confounder, effect modifier or main exposure of interest (Benmarhnia et al. 2021) (Figure 1). Considering RE as a confounder (e.g., including RE as a covariate in the model) acknowledges that differential exposure and health disparities exists across racial and ethnic groups, but regards such disparities as non-manipulable through a "ritualistic adjustment" (Kaufman 2014; VanderWeele and Robinson 2014), while masking systematic racism manifested through air pollution (Swilley-Martinez et al. 2023). Only adjusting RE as a confounder also precludes consideration of differential susceptibility. However, considering RE as a confounder is still the most common usage of RE in air pollution-related health studies. For example, 46 (73%) out of 63 identified studies only considered RE as a confounder in a review on the association between particulate matter and adverse birth outcomes with some considerations of RE (Thayamballi et al. 2021).

Figure 1 Schematics depicting the study types considered in this review



When RE is considered an effect modifier in the association between an environmental exposure and a health outcome (including stratified analysis by RE or interaction terms between air pollution and RE) (Figure 1B, effect modification [EM] analysis), both differential exposure and differential susceptibility are incorporated into the analysis, but the challenge remains in the interpretation of the observed disparity in the health effect of air pollution. A recent review of ten US-based empirical air pollution-related health studies that considered RE from 2016 to 2022 found a lack of in-depth discussion of such disparity (Hicken et al. 2023). Perry et al. connected this lack of conceptual discussion to the origin of mainstream environmental health studies, in which RE was usually considered as a biological determinant and the observed health disparity was considered evidence of inferiority of the racial and ethnic minorities. Besides, considering RE as an effect modifier of air pollution related health impact is still a relatively rare practice, occurring in 16 (13%) out of 124 studies of air pollution-related pregnancy outcomes from 1990 to 2024 (Dzekem et al. 2024). On a related note, a few methodological ambiguities exist on the distinction between interaction and effect modification (VanderWeele 2009), and the application of formal heterogeneity tests (Kaufman and MacLehose 2013).

When RE is used as the main exposure of interest, the study could either focus on quantifying the differential exposure (i.e., including air pollution as the outcome without considering health) (Figure 1A, exposure disparity analysis) or on decomposing the total effect of RE on a health outcome to an indirect part mediated through differential exposure to air pollution and a direct part representing the effect of RE through other pathways (Figure 1C, mediation analysis). Similar to studies with RE considered as an effect modifier, proper interpretation of the observed disparity in air pollution is a major challenge for the first type of study and incorporation of a conceptual framework is crucial. A recent review on environmental justice studies of any environmental pollutants published between 2018 and 2021 found a lack of framework in 98 (47%) out of 208 exposure-only disparity studies. The second type of study, decomposition analysis, a special type of mediation analysis, asks a simple question: how disparities in the health outcome would change if disparities in the mediator (e.g., air pollution) were removed (Jackson 2021). Although causal decomposition analysis is gaining popularity in mainstream epidemiological studies as it combines intervention and health disparity through the counterfactual framework, its usage remains rare in air pollution-related health studies. For example, the review of environmental justice studies of any environmental pollutants from 2018 to 2021 found that only 5 (2.6%) out of 194 identified epidemiological studies used mediation analysis (Casey et al. 2023). Besides, there are many assumptions and challenges in the application of decomposition analysis that impedes its application, including incorporation of clear causal framework and the interpretation around manipulability of RE (Benmarhnia et al. 2021).

Aside from challenges specific to each type of RE usage, there are other inferential and methodological challenges in the use of RE in air pollution-related health studies. First, the operationalization of RE requires careful consideration (Martinez et al. 2023). For example, the usage of an ambiguous "other" category without justification masks the heterogeneity in experiences of minority groups (Martinez et al. 2023). Nevertheless, RE is tightly intertwined with socioeconomic factors and how to understand the disparity across RE with considerations of socioeconomic factor remains a controversial topic (Hajat et al. 2021). Understanding how multiple social identities like RE and socioeconomic factors may interact and affect air pollution-related health is another important consideration. One proposed approach to unpack such complexity is using intersectional decomposition analysis discussed above to disentangle the contribution from different factors on the individual experience (Jackson 2021).

Aims of this report

Here, we focused on California, the most populated state of the U.S. facing a complicated air pollution challenge. Although California has progressive air pollution control policies (Karmel and FitzGibbon; Lurmann et al. 2015), it also has the highest number of counties that exceed the U.S. Environmental Protection Agency's air quality standards (EPA) for ambient fine particulate matter and ozone. These non-attainment areas are mostly located in the Central Valley area and Los Angeles metropolitan area, where high agricultural and transportation activities exist. California also experiences a changing landscape for air pollution due to increases in wildfire smoke-related air pollution, which already constituted more than 50% of primary fine particulate matter in California and is projected to increase as climate change progresses (Burke et al. 2023; Ford et al. 2018). With its complex air pollution challenge and a highly diverse population (40% Latino, 35% white, 15% Asian or Pacific Islander, 5% Black, 4% multiracial, and fewer than 1% Native American or Alaska Natives) (California's Population), California has been at the forefront of understanding the role of race and ethnicity in health disparity studies. Understanding the operationalization of RE in California air pollution-related health studies could provide relevant insights for all U.S. regions, especially as climate change progresses and wildfire become more prevalent.

As suggested by Payne et al. and Casey et al., centering environmental justice questions in environmental health sciences is essential and could be facilitated by providing a guideline on the use of RE. In this report, we aimed to summarize the use of RE in air pollution epidemiology literature in California and make methodological recommendations. With this aim in mind, we first conducted a scoping review to understand the landscape on the use of RE in air pollution-related health studies in California. Next, we summarized important methodological considerations and assumptions in air pollution-related health study with different operationalization of RE. We not only provided recommendations for researchers on the use of RE, but also equipped policymakers and the public with a better understanding of current practices in the use of RE in air pollution-related studies, including the assumptions and conceptual frameworks.

Methods

Based on the PRISMA Extension for Scoping Review (Tricco et al. 2018), we conducted the scoping review in five steps: eligibility criteria establishment, initial search for eligible articles, abstract and title screening, full-text review, and data extraction. At least two researchers (CC, AKD, SZ, or RG) participated in each step and consensus was achieved in every step.

Eligibility criteria

We aimed to identify and summarize peer-reviewed articles on empirical population studies of air pollution that considered RE other than a confounder. This led to a focus on three major types of study shown in Figure 1: air pollution exposure disparity study across RE (exposure disparity analysis), air pollution-outcome association modified by RE (effect modification analysis), and outcome disparity across RE with air pollution as a mediator (mediation analysis). We did not include articles that only considered RE as a confounder for the air pollution-health outcome relationship due to the high prevalence of such practice and the preclusion of systematic racism manifested through air pollution (Swilley-Martinez et al. 2023).

We created a list of eligibility criteria to guide the process (Table 1). To restrict the review to a manageable size, we decided *a priori* to focus on ambient air pollutants including the six criteria air pollutants (US EPA 2014), wildfire-related air pollution, and air quality index. These air pollutants could be treated as an exposure (effect modification analysis), outcome (exposure disparity analysis), or mediator (mediation analysis) in the study. Additionally, we required that RE be included as an exposure (exposure disparity analysis or mediation analysis) or effect modifier (effect modification analysis). We did not impose any restriction on the health outcomes and considered studies evaluating the differential exposure to air pollutants across RE. We also limited our review to articles published between January 1, 2000, to December 31, 2023, and conducted within California or with a general focus on the United States.

To further clarify the eligibility criteria, we created a list of exclusion criteria (Table 1). For example, we excluded occupational cohorts (including studies focusing exclusively on farmworkers or firefighters), animal studies, health impact assessments that relied solely on concentration-response functions estimated by other studies, exposure disparity studies relying solely on exposure simulation, and non-population-based studies involving experimental or randomized exposure schemes. We also excluded studies that focused on indoor air pollution, smoking, or ambient air pollutants other than those listed in the eligibility criteria.

Table 1: Eligibility criteria and corresponding exclusion criteria for the scoping review.

Eligibility Criteria	**Exclusion Criteria**
1. English language	1. Not in English
2. Peer-reviewed empirical population studies published as journal articles	2. Reviews, commentaries, letters, editorials, news and case reports, conference papers, pre-prints
3. Publication year between 2000/1/1 and 2023/12/31	3. Published before 2000/1/1 or after 2023/12/31
4. Must be conducted within California or a general focus on the US	4. Exclusively focusing on an area outside of California (e.g., Europe, east coast of US or Florida)

5. Must use ambient air pollution (six criteria air pollutant, wildfire, air quality index) as exposure, outcome or mediator 6. Must include Table 1 and ethnicity as exposure (when air pollution is the outcome) or effect modifier or mediator	5. Occupational cohorts, animal studies, health impact assessment, simulation studies, or non-population-based studies (i.e. those that involved experimental or randomized exposure schemes) 6. Race and ethnicity is used as a confounder 7. Air pollution is used as a confounder 8. Focused on indoor air pollution, smoking, or ambient air pollutants other than ones specified.

Initial search

Based on the eligibility criteria, we selected search terms for four databases (PubMed, Embase, Web of Science, and CINHAL). Briefly, we created separate sets of search terms for air pollution, RE, geographical areas, and article type. We applied these search terms to a search of the title and abstract, and identified articles satisfying all sets of terms simultaneously. We included the detailed search terms used for each database in the appendix (Supplementary Table 1) and applied the publication date restriction manually. The initial search strategy yielded 3,898 articles from the four databases (1,242 from PubMed, 1,111 from Embase, 1,365 from Web of Science, and 180 from CINHAL).

To increase the comprehensiveness of our initial search, we also added potentially eligible original articles cited in relevant reviews and California Air Resources Board (CARB) reports to our initial search results. Briefly, we searched the four databases with similar search terms as described above but primed to identify reviews as compared to focusing on original articles (Supplementary Table 2). This search yielded 163 review articles, and we further identified 37 relevant ones through abstract and title review based on the eligibility/exclusion criteria (Table 1). We also identified four relevant CARB reports through abstract and title review (

Supplementary Table 3). Next, we read the full text of the review articles and CARB reports to identify the final list of 33 articles to extract relevant cited articles from. Two researchers (CC and AKD) independently conducted the abstract and title screening and full-text review. Conflicts were resolved through discussion. Prior to beginning the formal screening process, the two researchers underwent a calibration exercise using five review papers not included in the study sample to ensure consistency in their selection approach. Any discrepancies in paper selection during this exercise were discussed to resolve conflicts and establish a standardized screening criterion. Finally, each researcher read half of the relevant reviews and identified potentially eligible original articles cited. We identified 248 articles and combined them with articles identified through database search for the screening stage (Figure 2). Among 4,146 articles identified, we excluded 2,242 duplicates and included 1,904 articles for abstract and title screening.

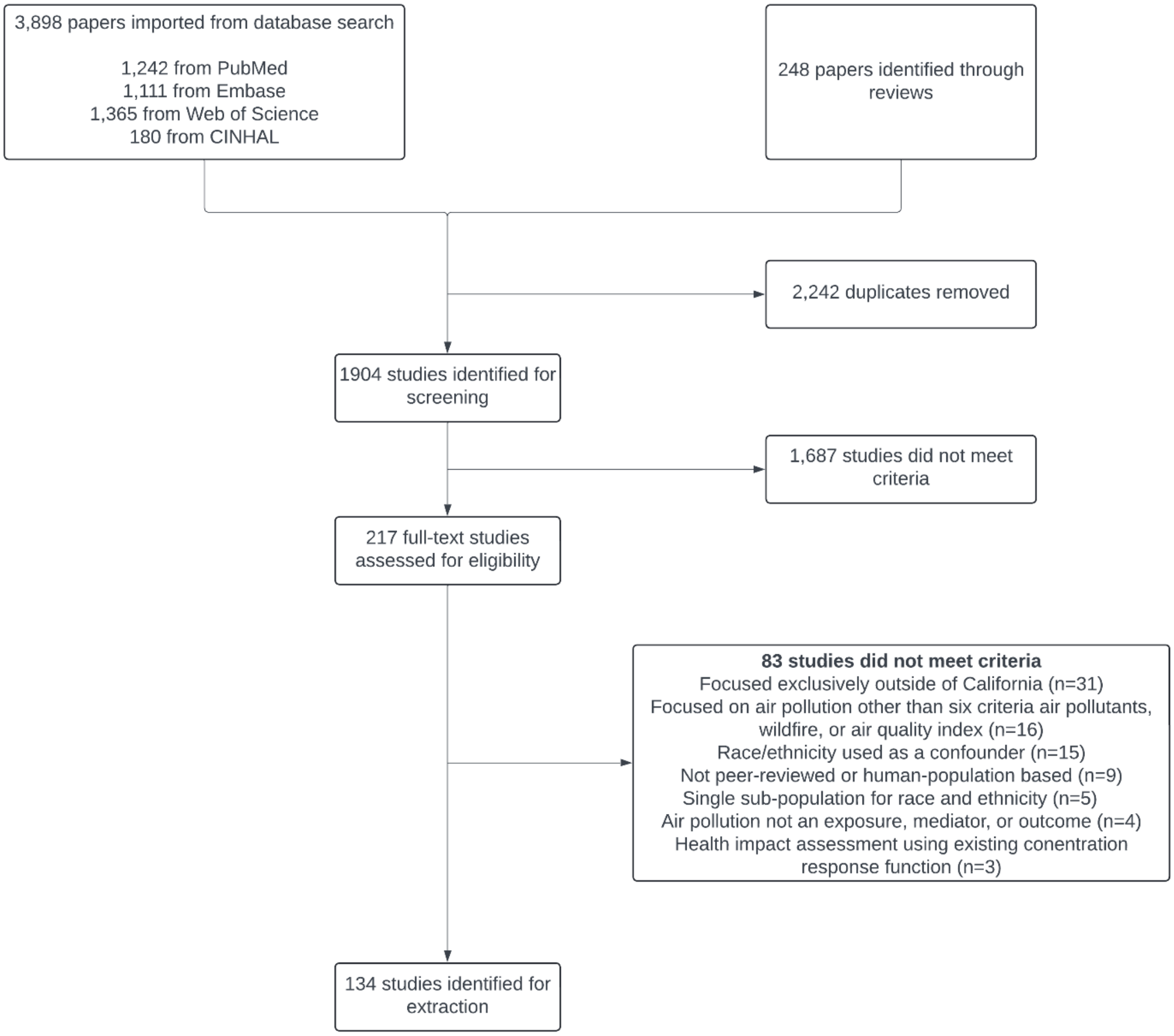


Figure 2 Flowchart of number of articles identified and screened at different stages of the review

Abstract and title screening

We conducted the abstract and title screening using the eligibility criteria and the derived exclusion criteria (Table 1). The screening process involved two screeners (SZ and RG) and one conflict resolver (CC or AKD). Prior to beginning the formal screening process, the two screeners (SZ and RG) completed a thorough training exercise using 10 research articles on similar topics that were not included in the study sample. This training ensured consistent application of screening criteria and familiarized the screeners with the decision-making process. Each screener could vote “yes”, “no”, or “maybe” to indicate their decision for each article. The article was excluded from the review process only when both screeners voted “no”. The article was sent for full-text review when both screeners voted “yes”. When either screener voted “maybe” or their votes were different, the article was marked as a conflict, and a conflict resolver reviewed the abstract and title to decide whether the article should be excluded or included for full-text review (Figure 3). We excluded 1,687 articles in this stage and included 217 articles for full-text review (Figure 2).

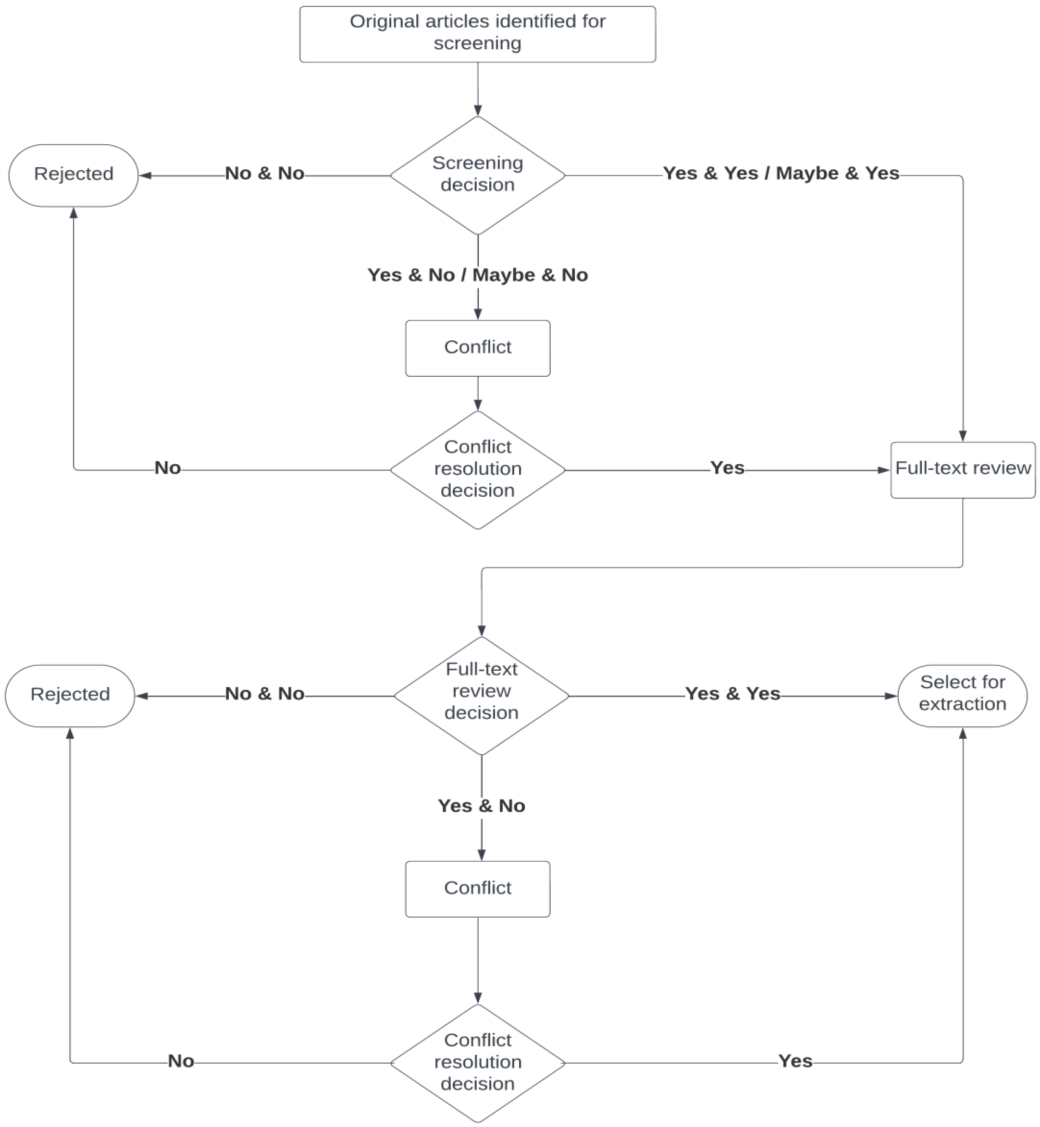


Figure 3: Flowchart detailing the process at the abstract-screening and full-text review stage

Full text review

We applied the same eligibility criteria and exclusion criteria at this stage. Two researchers (CC and AKD) independently voted yes/no for inclusion after reading the full article. Conflicts were resolved through discussion between the two researchers (Figure 3). This process led to the exclusion of 83 articles and the remaining 134 articles were included in the study (Figure 2). Reasons for exclusion included studies conducted exclusively outside of California (n=31), studies focused on air pollutants other than the six criteria air pollutants, wildfire, or air quality index (n=16), and studies that used RE as a confounder (n=15). Additional exclusions were made for non-peer-reviewed or non-human population studies (n=9), studies examining only a single racial and ethnic subpopulation (n=5), studies where air pollution was not considered as an exposure, mediator, or outcome (n=4), and health impact assessments that solely used existing concentration-response functions (n=3) (Figure 2).

Data extraction

We created a data extraction form to collect information on basic study characteristics and important methodological considerations for these types of studies (Benmarhnia et al. 2021; Casey et al. 2023; Martinez et al. 2023). Two researchers (CC and AKD) independently extracted information from each article and reached consensus on discordant items via discussion. An empty extraction form is shown in Supplementary material.

First, we extracted general information (e.g. study title, author, year of publication) and basic study characteristics such as study period, geographic location, and the number of participants. We also classified articles as air pollution exposure disparity across RE study (exposure disparity), air pollution-outcome association modified by RE (effect modification analysis), and outcome disparity across RE with air pollution as a mediator (mediation analysis). We also extracted detailed information on variables used for air pollution, RE, and income. We documented how each of these variables were used in the study (e.g. as an exposure, outcome, potential effect modifier, or mediator), as well as the source, and spatial and temporal resolutions of these variables.

For air pollution variables, we also identified the pollutant(s) explored in the study and specified the estimation of exposure data (e.g., monitors alone [i.e., with simple spatial assignment methods that does not include information other than location of the monitor, such as average within a geographic area or nearest location assignment], satellite data alone, emission inventory data alone, statistical models, dynamic models [e.g., chemical transport model], and a combination of several methods).

For RE variables, we extracted the measurement methods based on categories outlined by Roth (e.g. self-reported vs. observed) and unit of analysis (e.g. individual level, proportion within an area, or area-level index). We extracted the specific racial and ethnic categories utilized in the study and whether one or more RE categories were collapsed or omitted from the original data. We also assessed whether the study incorporated additional forms of RE variables beyond the primary measure of RE and summarized their intended functions in analysis (e.g., as confounders or region-level covariates). We also evaluated whether authors provided justification for including the additional RE variables and documented their stated rationale when available.

Although many different indicators were used to represent the social and economic factors that influence individuals' or groups' exposure and susceptibility towards air pollution (e.g., income, poverty, education, and composite SES indicators) (Hajat et al. 2021), we focused on variables directly describing income or poverty to focus explicitly on the material resources aspect of their socioeconomic position.

Next, we extracted information specific to each study type. For studies examining exposure disparities, we identified the analytical approaches employed, categorized as univariable regression, multivariable regression, or descriptive metrics of outcome (e.g., population-weighted averages).

For studies of health disparities, either considering RE as potential effect modifier for air pollution-health relationship or examining the disparity through mediation analysis, we documented the study design (i.e., ecological, time-series/ecological, cross-sectional, case-control, or cohort study). For effect modification studies, we additionally recorded the primary analytical approaches (i.e., multivariable regression models, multilevel models, G-methods, or machine learning/predictive models). We also noted whether authors explicitly used epidemiological terminology (e.g., effect modification and effect heterogeneity) or statistical terminology (e.g., interaction terms and stratified analysis), whether formal heterogeneity testing was performed, and how results were reported with and without significant heterogeneity test. Additionally, we captured methodological nuances such as the incorporation of multiple community characteristics in secondary stage models (e.g., time series or Bayesian hierarchical models) and whether authors mentioned potential confounding of the effect modifier by other variables.

We also assessed a few potential methodological concerns in exposure disparity study and effect modification study. Specifically, we evaluated whether authors interpreted coefficients of variables other than the exposure of interest from the same model, which could introduce Table 2 fallacy in health disparity studies due to potential bias in the coefficients of control variables. We also examined whether studies intentionally considered the intersectionality of RE and income in their analyses, distinguishing this from cases where income was merely included as a confounder in RE-stratified models. For studies that explicitly addressed intersectionality, we documented their methodological approach.

For studies using mediation analysis, we assessed three major methodological concerns based on the guideline for reporting mediation analyses (AGReMA statement) (Lee et al. 2021). First, we assessed if the authors included rationales for conducting the mediation analysis and discussed the inferences for their results. Second, we evaluated whether the study clearly specified the causal framework. Third, we identified the analytical method and evaluated the discussion of causal identification assumptions in such methods (e.g., does this method allow interaction between exposure and mediator and intermediate confounders). We also extracted whether a specific package was used to carry out the analysis. We did not incorporate this information extraction for mediation analysis into the extraction form given the expected small number of studies and high variability in methodology under this type.

Finally, we summarized the key findings from each article. We also evaluated how studies contextualized and interpreted their findings. We extracted key discussion points related to RE disparities and assessed whether authors provided substantive discussion of their findings and whether they employed a conceptual framework (such as structural racism or historical discriminatory practices) to explain the observed disparities. Similarly, for studies that considered income variables, we documented whether authors explicitly discussed their income-related results and extracted their interpretative framework for understanding the observed socioeconomic disparities. Understanding the conceptual frameworks allowed us to assess how studies situated their empirical findings within broader theoretical and social contexts.

Results

Basic study characteristics

Among 134 studies extracted, 82 (61.2%) focused on the entire US or a representative sample of the US, while 42 (31.3%) focused specifically on California or regions within California (Supplementary Table 4). The remaining 10 studies (7.5%) included some California regions in addition to other states but were not representative of the entire country. In terms of study type, 79 studies (59.0%) studies examined effect modification (EM) analysis, and 49 studies (36.6%) examined exposure disparity. Of the remaining six studies, three explored mediation analysis (Benmarhnia et al. 2017; Jones et al. 2015; Song et al. 2020a), one study evaluated examined exposure disparity and also examined mediation (Woodruff et al. 2003a), and two studies examined both EM and mediation analysis (Yannatos et al. 2023a; Younan et al. 2022a). We thus had a total of 50 exposure disparity studies, 81 EM analysis, and 6 studies that assessed mediation analysis.

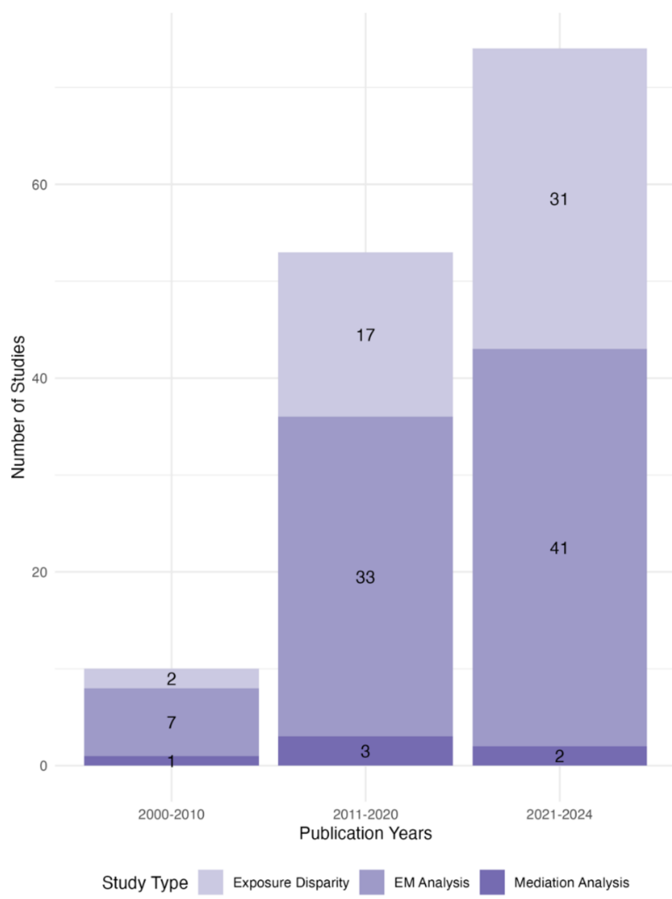


Figure 4 Number of studies published by type of study and across publication years

There is an increase in the number of publications across study types other than health disparity study with mediation over the years, with 74 (55.2%) published between 2021-2024, followed by 53 (39.6%) published between 2011-2020, and only 10 (7.5%) published between 2000-2010. This temporal pattern was consistent across study types, with the highest proportion of publications occurring in 2021-2024 for studies exploring exposure disparity (62.0%), studies assessing EM analysis (50.6%), and studies assessing mediation analysis (33.3%). Notable growth was observed between the first two decades (2000-2020) and the most recent period (2021-2024), particularly for exposure disparity studies, which increased from just 2 studies (4.0%) in 2000-2010 to 31 studies (62.0%) in 2021-2024. Studies assessing EM analysis showed a similar trend, increasing from 7 studies (8.6%) in 2000-2010 to 41 studies (50.6%) in 2021-2024, while mediation analyses emerged primarily after 2011 (Figure 4).

Use of air-pollution across study types

The majority of studies examined a single pollutant (71 studies, 53.0%), while fewer studies investigated multiple pollutants: 30 studies (22.4%) examined two pollutants, 18 studies (13.4%) looked at three pollutants, and 15 studies (11.2%) analyzed four or more pollutants. This pattern was generally consistent across different study types, though with some variations. Among studies exploring exposure disparity, the preference for single-pollutant analyses was even more pronounced, with 60.0% examining one pollutant, 28.0% studying two pollutants, and relatively few investigating three (8.0%) or four or more pollutants (4.0%). Studies assessing EM analysis (N=81) showed a more balanced distribution, with 50.6% examining single pollutants and a notable proportion analyzing multiple pollutants: 17.3% for two pollutants, and 16.0% each for three pollutants and four or more pollutants. The six studies that assessed mediation analysis were evenly split between examining one, two, and three pollutants (33.3% each), with none analyzing four or more pollutants (Table *2*).

Table 2 Number of air pollutants considered across study type

Study Characteristics	**All studies (N = 134)**	**Exposure disparity studies (N = 50)**	**EM analysis studies (N = 81)**	**Mediation analysis studies (N = 6)**
Number of pollutants used				
Single pollutant	71 (53.0%)	30 (60.0%)	41 (50.6%)	2 (33.3%)
Two pollutants	30 (22.4%)	14 (28.0%)	14 (17.3%)	2 (33.3%)
Three pollutants	18 (13.4%)	4 (8.0%)	13 (16.0%)	2 (33.3%)
4 or more pollutants	15 (11.2%)	2 (4.0%)	13 (16.0%)	0 (0.0%)
[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.				

Across all studies, fine particulate matter ($PM_{2.5}$) was the most commonly studied pollutant, examined in 100 (74.6%) studies, followed by nitrogen dioxide (NO_2) in 47 (35.1%) studies and ozone in 28 (20.9%) studies. Coarse particulate matter (PM_{10}) was investigated in 16 (11.9%) studies, while other criteria pollutants such as NOx, carbon monoxide (CO), and sulfur dioxide (SO_2) were examined in 14 (10.4%), 9 (6.7%), and 5 (3.7%) studies, respectively. $PM_{2.5}$ constituents/components were studied in 8 (6%) studies, and several studies focused on specific source categories of $PM_{2.5}$, including source-apportioned $PM_{2.5}$, traffic-related $PM_{2.5}$, non-traffic $PM_{2.5}$, particulate matter from coal, and diesel PM emission (each in 1-2 studies). Ultrafine particles, wildfire smoke, and lead were each investigated in 5 (3.7%), 5 (3.7%), and 4 (3%) studies, respectively. Black carbon and benzene were examined in 3 (2.2%) studies, while elemental carbon was studied in 2 (1.5%) studies. Other less common pollutants included air quality index (AQI), anthropogenic NO_2, CO_2, traffic exposure approximated by proximity to roads, traffic-related NO_x, and traffic-related PM (each in 1 study, 0.7%) (

Supplementary Table 5).

The studies utilized various approaches to assess air pollution exposure. The most common approach was statistical modeling (54 studies, 40.3%), followed equally by dynamic model-based approaches and monitoring data alone (31 studies each, 23.1%), a combination of statistical and dynamic models (7 studies, 5.2%), satellite data alone (2 studies, 1.5%), and emission inventory data alone (2 studies, 1.5%) (Table 3). Multiple methods were used in 5 studies (3.7%), and the approach was not discussed in 2 studies (1.5%). Among seven studies that combined statistical model and dynamic model, three specifically employ machine learning algorithms (i.e., neural network models). Satellite products utilized are TROPOMI-based NO_2 measurements, NOAA's Hazard Mapping System based smoke plume detection, and the United States Forest Service Wildfire Hazard Potential based wildfire hazard detection. One particularly comprehensive study compared eight different exposure estimation techniques, including chemical transport model, interpolation method, satellite-derived method, Bayesian statistical regression, and machine learning approach (Kelly et al. 2021) (Table 3).

The temporal resolution of exposure assessment varied, with yearly averages being the most common (58 studies, 43.3%), followed by study-specific periods (20 studies, 14.9%) and daily measurements (18 studies, 13.4%). Averages of multiple years were used in 14 studies (10.4%). A notable number of studies (10 studies, 7.5%) used exposure periods related to pregnancy, gestation, or birth. Monthly measurements were less common, used in only 4 studies (3.0%). Some studies employed specific temporal windows related to study events, such as periods prior to enrollment (3 studies, 2.2%) or censoring events (4 studies, 3.0%). Moving averages were used in 3 studies (2.2%). These patterns varied by study type - for instance, among studies exploring exposure disparity, yearly averages were particularly dominant (29 studies, 58.0%), while studies assessing EM analysis showed more diverse temporal resolutions, with a notably higher proportion using daily measurements (16 studies, 19.8%). Studies involving mediation analysis predominantly used yearly averages (4 studies, 66.7%) (Table 3).

Table 3 Source and temporality of air pollution data across study types

Study Characteristics	All studies (N = 134)	Exposure disparity studies (N = 50)	EM analysis studies (N = 81)	Mediation analysis studies (N = 6)
Source of Air Pollution Data				
Statistical modeling	54 (40.3%)	22 (44.0%)	30 (37.0%)	2 (33.3%)
Dynamic model-based approach	31 (23.1%)	11 (22.0%)	20 (24.7%)	1 (16.7%)
Monitoring data alone	31 (23.1%)	8 (16.0%)	22 (27.2%)	2 (33.3%)
Combination of statistical and dynamic model	7 (5.2%)	4 (8.0%)	3 (3.7%)	0 (0.0%)
Satellite data only	2 (1.5%)	2 (4.0%)	0 (0.0%)	0 (0.0%)
Emissions inventory data only	2 (1.5%)	2 (4.0%)	0 (0.0%)	0 (0.0%)
Other: Multiple methods	5 (3.7%)	1 (2.0%)	4 (4.9%)	0 (0.0%)
Not discussed	2 (1.5%)	0 (0.0%)	2 (2.5%)	1 (16.7%)
Temporal Unit of Air Pollution Data				
Daily	18 (13.4%)	2 (4.0%)	16 (19.8%)	0 (0.0%)
Monthly	4 (3.0%)	0 (0.0%)	4 (4.9%)	0 (0.0%)
Yearly	58 (43.3%)	29 (58.0%)	27 (33.3%)	4 (66.7%)
Average of multiple years	14 (10.4%)	9 (18.0%)	5 (6.2%)	1 (16.7%)
Related to pregnancy/gestation/birth	10 (7.5%)	0 (0.0%)	10 (12.3%)	0 (0.0%)
Study specific period prior to enrollment event	3 (2.2%)	0 (0.0%)	3 (3.7%)	0 (0.0%)
Study specific period prior to censoring event	4 (3.0%)	0 (0.0%)	4 (4.9%)	0 (0.0%)
Moving averages	3 (2.2%)	0 (0.0%)	3 (3.7%)	0 (0.0%)
Specific to study period	20 (14.9%)	10 (20.0%)	9 (11.1%)	1 (16.7%)

[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.

The geographical resolution of air pollution data includes administrative unit level (94 studies, 70.2% - sum of all admin units), individual or residential address level (24 studies, 18.0%), grid cell levels (10 studies, 7.5%), site-specific level (4 studies, 3.0%), and air basins (1 study, 0.8%) (Table 4). Administrative units utilized are ZIP code/ZCTAs (34 studies, 25.6%), census tracts (21 studies, 15.8%), census block groups (10 studies, 7.5%), census blocks (6 studies, 4.5%), counties (16 studies, 12.0%), Metropolitan/Core Based Statistical Areas (2 studies, 1.5%), county groups (1 study, 0.8%), parcel level (1 study, 0.8%), and state level (2 studies, 1.5%). Grid-based approaches varied in resolution, from fine-scale 30m block segments to larger 48km rural grids, with several studies using variable resolution grids that were finer in urban areas (e.g., 1km) and coarser in rural areas (e.g., 48km). Site specific studies utilized study site locations (e.g., schools, parks). Notable differences emerged between study types: exposure disparity studies had higher use of census tracts (30.0%) and grid-based approaches (20.0%), while studies assessing EM analysis more commonly utilized ZIP Code/ZIP Code Tabulation Area (ZCTA) (38.8%) and individual level data (26.3%) (Table 4).

Table 4 Geographical units of air pollution variables used across studies

Study Characteristics	All studies (N = 134)	Exposure disparity studies (N = 50)	EM analysis studies (N = 81)	Mediation analysis studies (N = 6)
Geographical Unit of Air Pollution Data				
Admin: Zip Code/ZCTA	34 (25.6%)	2 (4.0%)	31 (38.8%)	1 (16.7%)
Admin: Census Tract	21 (15.8%)	15 (30.0%)	6 (7.5%)	1 (16.7%)
Admin: Census Block	6 (4.5%)	5 (10.0%)	1 (1.3%)	0 (0.0%)
Admin: Census Block Group	10 (7.5%)	8 (16.0%)	2 (2.5%)	0 (0.0%)
Admin: County	16 (12.0%)	3 (6.0%)	13 (16.3%)	1 (16.7%)
Admin: County Groups	1 (0.8%)	0 (0.0%)	1 (1.3%)	0 (0.0%)
Admin: Metropolitan/Core Based Statistical Area	2 (1.5%)	1 (2.0%)	1 (1.3%)	0 (0.0%)
Admin: State	2 (1.5%)	0 (0.0%)	2 (2.5%)	0 (0.0%)
Admin: Multiple Admin Units	1 (0.8%)	1 (2.0%)	0 (0.0%)	0 (0.0%)
Admin: Parcel	1 (0.8%)	1 (2.0%)	0 (0.0%)	0 (0.0%)
Individual (Or Residential Address)	24 (18.0%)	1 (2.0%)	21 (26.3%)	3 (50.0%)
Grid Based	10 (7.5%)	10 (20.0%)	0 (0.0%)	0 (0.0%)
Other: Site Specific	4 (3.0%)	3 (6.0%)	1 (1.3%)	0 (0.0%)
Other: Air-Basin	1 (0.8%)	0 (0.0%)	1 (1.3%)	0 (0.0%)

[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.

Use of RE variables across study types

The source, method of collection, and characterization of RE data varied substantially across studies. Medical records were the most common source of RE data (48 studies, 35.8%), followed closely by general population surveys such as the American Community Survey (45 studies, 33.6%), while 27 studies (20.1%) collected data directly within their cohorts (Table 5). Self-reported RE was the predominant collection method (82 studies, 61.2%), though notably, 50 studies (37.3%) did not discuss their collection method. The level of RE data also differed by study type: exposure disparity studies primarily used area-level proportions (80.0%), while EM analysis studies predominantly used individual-level data (90.1%). Regarding data handling, 60 studies (44.8%) explicitly reported combining multiple RE categories, while for 66 studies (49.3%), the handling of RE categories was unclear (existed in the all three periods. The prevalence of studies not reporting their handling of RE category was 78%, 60%, and 51% for 2000-2010, 2011-2019, and 2020-2024, respectively (Table 5).

Table 5 Sources and characteristics of RE data across study types

Study Characteristics	All studies (N = 134)	Exposure disparity studies (N = 50)	EM analysis studies (N = 81)	Mediation analysis studies (N = 6)
Source of RE data				
Data collected within the cohort (e.g., enrollment questionnaire)	27 (20.1%)	5 (10.0%)	20 (24.7%)	4 (66.7%)
Data product (e.g., CalEnviroScreen, Healthy Place Index)	9 (6.7%)	5 (10.0%)	4 (4.9%)	0 (0.0%)
General population survey (e.g., American community survey, Decennial Census survey)	45 (33.6%)	38 (76.0%)	7 (8.6%)	0 (0.0%)
Medical record (e.g., cancer registry, hospitalization)	48 (35.8%)	1 (2.0%)	46 (56.8%)	2 (33.3%)
Not discussed	5 (3.7%)	1 (2.0%)	4 (4.9%)	0 (0.0%)
Method of collecting RE data				
Self-report	82 (61.2%)	46 (92.0%)	33 (40.7%)	5 (83.3%)
Not discussed	50 (37.3%)	4 (8.0%)	46 (56.8%)	1 (16.7%)
Other	2 (1.5%)	0 (0.0%)	2 (2.5%)	0 (0.0%)
Type of RE data				
Individual level	83 (61.9%)	7 (14.0%)	73 (90.1%)	6 (100.0%)
Proportion of R/E within an area	46 (34.3%)	40 (80.0%)	6 (7.4%)	0 (0.0%)
Other	5 (3.7%)	3 (6.0%)	2 (2.5%)	0 (0.0%)

[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.

Few studies (28, 20.9%) included RE data in other forms as stratification or interaction terms (Supplementary Table 6). Among them, 20 explicitly stated their justification for including additional RE data, with the most common reasons being residential patterns and segregation (4 studies citing it as "an important driver of exposure inequality" and a capture of "multiple adverse social and psychosocial exposures"), methodological considerations (3 studies mentioning confounding control), and policy relevance (3 studies referencing environmental justice decisions and regulatory enforcement). Other justifications included the need to investigate spatial patterns based on administrative boundaries, explain heterogeneity in associations, address macro-social forces affecting neighborhood pollution over time, and enable analyses disaggregated by both RE and income. Some studies cited multiple reasons, reflecting the complex interplay between RE factors and air pollution exposure patterns.

In examining the RE categorizations used across 134 studies, "Asian, Black, Hispanic, White" was most prevalent (20.15%, n=27), followed by "Black, White" (8.96%, n=12) and "Black, Hispanic, White" (8.21%, n=11). Other common combinations were "Asian, Black, Hispanic, Other, White" (6.72%, n=9) and "Black, Other, White" (5.22%, n=7). A few papers used "Asian/PI, Black, Hispanic, White" and "Black, non-Black" combinations (2.99%, n=4 each). Some studies employed highly specific categorizations like "Black, Cuban, Dominican, Hispanic, Mexican, Puerto Rican, White-Hispanic" (0.75%, n=1), while others used binary classifications such as "POC, White" or "non-minority, RE minority" (Supplementary Table 7). One study utilized "Social Vulnerability Index", an area-level composite score incorporated socioeconomic status, race and ethnicity and language, household composition and disability, and housing and transportation.

Use of Income across study types

Income was frequently included in air pollution studies considering RE (92 studies, 68.7%). This pattern was relatively consistent across study types, with income being included in 36 exposure disparity studies (72.0%), 54 EM analysis studies (66.7%), and 4 mediation analysis studies (66.7%). The high proportion of studies considering income reflects a common awareness that socioeconomic factors and RE are intertwined in air pollution studies (Table 6).

Table 6 Use of income across study types

Study Characteristics	All studies (N = 134)	Exposure disparity studies (N = 50)	EM analysis studies (N = 81)	Mediation analysis studies (N = 6)
Income included				
Yes	92 (68.7%)	36 (72.0%)	54 (66.7%)	4 (66.7%)
No	42 (31.3%)	14 (28.0%)	27 (33.3%)	2 (33.3%)

[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.

Most studies that included income relied on general population surveys (66.3%) to obtain the income information and used area-level income measures (82.6%) rather than individual/household measures. Notably, while most studies discussed their income-related findings (87%), only a small proportion (19.6%) considered intersectionality between income and RE. This pattern varied by study type, with exposure disparity studies more likely to consider intersectionality (38.9%) compared to EM analysis studies (7.4%) (Table 7).

Table 7 Details of the income variable used across study types

Study characteristics	All studies that used income (N = 92)	Exposure disparity studies that used income (N = 36)	EM analysis studies that used income (N = 54)	Mediation studies that used income (N = 4)
Source of Income data^				
General population survey (e.g., American community survey, Decennial Census survey)	61 (66.3%)	30 (83.3%)	31 (57.4%)	0 (0.0%)
Data collected within the cohort (e.g., enrollment questionnaire)	17 (18.5%)	4 (11.1%)	11 (20.4%)	4 (100.0%)
Data product (e.g., CalEnviroScreen, Healthy Place Index)	14 (15.2%)	3 (8.3%)	11 (20.4%)	1 (25.0%)
Not discussed	3 (3.3%)	0 (0.0%)	3 (5.6%)	0 (0.0%)
Other	1 (1.1%)	0 (0.0%)	1 (1.9%)	0 (0.0%)
Level of aggregation of income data^				
Individual/household level	20 (21.7%)	5 (13.9%)	13 (24.1%)	4 (100.0%)
Area level	76 (82.6%)	32 (88.9%)	44 (81.5%)	1 (25.0%)
Considered intersectionality between income and RE				
Yes	18 (19.6%)	14 (38.9%)	4 (7.4%)	0 (0.0%)
No	74 (80.4%)	22 (61.1%)	50 (92.6%)	4 (100.0%)
Discussed findings on Income				
Yes	80 (87.0%)	33 (91.7%)	45 (83.3%)	4 (100.0%)
No	12 (13.0%)	3 (8.3%)	9 (16.7%)	0 (0.0%)

^ Percentages do not sum to 100 due to multiple selections being allowed.

Methodological details by study type

Exposure disparity studies

Among the 50 studies that explored air pollution exposure disparities across RE, descriptive metrics of air pollution (56.0%) and multivariable regression analyses (40.0%) are most common analytical methods. Other analytical approaches employed including univariable regression, three-level hierarchical linear mixed models, univariable quantile regression, examining demographic patterns in areas with extreme air quality conditions, clustering analysis, and visualization methods. Examples of visualization methods included complementary cumulative distribution functions for two air pollutants and spatial distribution of air pollutant exposure among different racial/ethnic groups. Some studies utilized multiple analytical approaches, often combining descriptive statistics with more complex regression analyses to examine racial/ethnic disparities in air pollution exposure.

EM analysis studies

Among the 81 studies that assessed EM analysis, cohort (33.3%) and cross-sectional (32.1%) designs were most common, followed by time-series/ecological (18.5%) and ecological studies (13.6%). Most studies (79.0%) explicitly mentioned effect modification or effect heterogeneity in their methods or results, while some studies only referred to statistical terms like interaction (4.9%) or stratification (16.0%). More than two-thirds of the studies (69.1%) conducted formal heterogeneity tests to assess differences in effect estimates across RE groups (Table 8).

Table 8 Design and analytical characteristics of air pollution studies that assessed health disparities using effect modification

Study Characteristics	EM analysis studies (N = 81)
Study Design	
Cross-sectional	26 (32.1%)
Cohort	27 (33.3%)
Ecological	11 (13.6%)
Time-series/Ecological	15 (18.5%)
Other	2 (2.5%)
Explicit Mention of Effect Modification/Effect Heterogeneity	
No, only mentioned interaction	4 (4.9%)
No, only mentioned stratfication	13 (16.0%)
Yes	64 (79.0%)
Conducted Heterogeneity Test	
No	25 (30.9%)
Yes	56 (69.1%)

Among studies that conducted a heterogeneity test (N = 56), a majority of studies detected significant heterogeneity between sub-groups (73.2%). Of studies detecting significant heterogeneity, most (37 out of 41, or 66.1%) reported stratum-specific results, while only 4 studies (7.1%) did not. Similarly, among studies that did not detect heterogeneity, 12 studies (21.4%) still reported stratum-specific results, while 3 studies (5.4%) did not report these results (Table 9).

We found a few EM analysis studies that discussed confounding on the effect modifier by another variable (6.2%) (Eum et al. 2022; Gharibi et al. 2019; Hicken et al. 2016; Jin et al. 2022; Tong et al. 2022). A few studies also included multiple community characteristics as effect modifiers in the second stage model of the Bayesian hierarchical model (2.5%) (Bell and Dominici 2008; Tong et al. 2022).

Table 9 Reporting of heterogeneity results

	EM analysis studies that conducted heterogeneity test (N = 56)	
	Detected significant heterogeneity (N = 41)	Did not detect heterogeneity (N= 15)
Reporting heterogeneity results		
Reported stratum-specific results	37 (66.1%)	12 (21.4%)
Did not report stratum-specific results	4 (7.1%)	3 (5.4%)

In terms of analytical approaches in EM analysis, multivariable regression models were overwhelmingly the most common analytical approach, used in 80.2% of studies. More sophisticated statistical methods were less frequently employed, with two-stage models used in 13.6% of studies and G-methods in 9.9% of studies. Other analytical approaches were rarely used, appearing in only 1.2% of studies. The strong preference for multivariable regression models suggests a relatively standardized approach to analyzing effect modification in air pollution epidemiology studies (Figure 5).

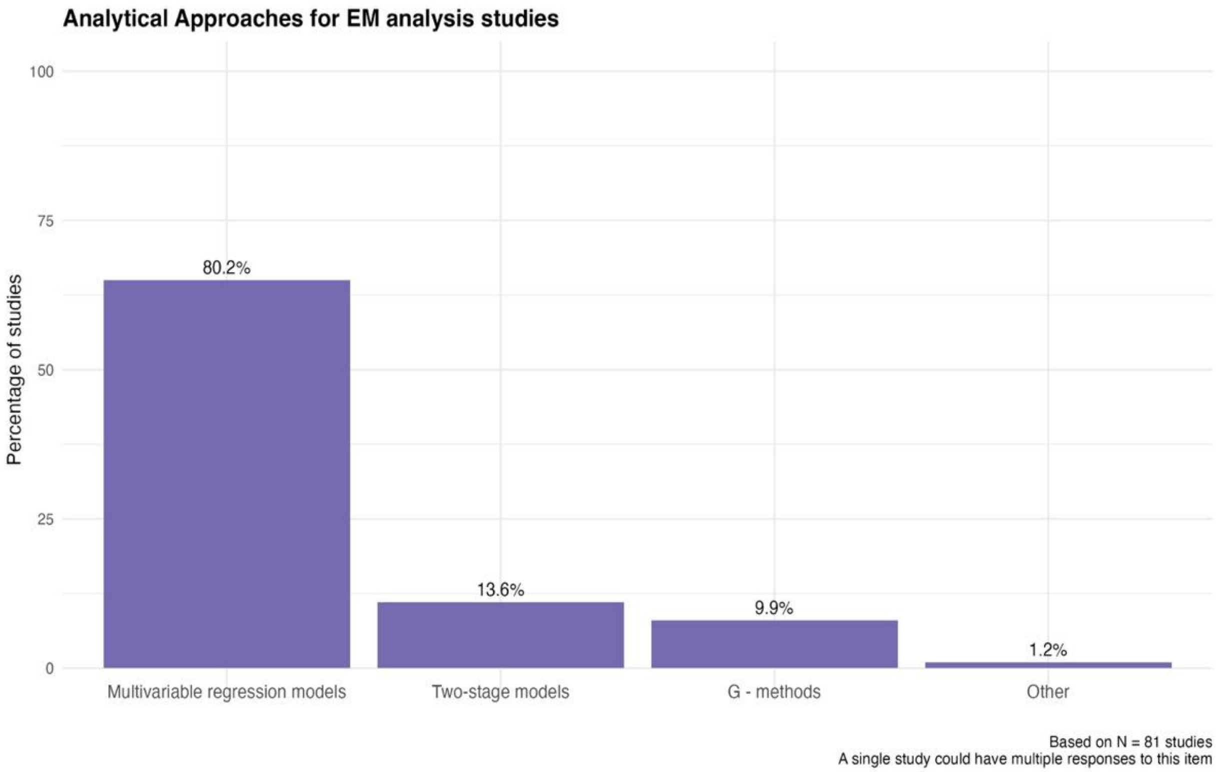


Figure 5 Analytical approaches for effect modification studies

Mediation analysis studies

All six studies that explored the role of air pollution as a potential mediator in the outcome disparity across RE provided subject matter rationales for such exploration and discussed the inferences of their results. However, none of them clearly stated the causal framework under which their analytical method was developed. Two studies utilized regression-based difference method without using any software package (VanderWeele 2016; Woodruff et al. 2003b; Younan et al. 2022b), two utilized regression-based product method with the "mediation" package in R or with STATA directly (i.e., the Baron-Kenny method) (Baron and Kenny 1986; Jones et al. 2015; Song et al. 2020b), and the other two used the Blinder-Oaxaca decomposition analysis with "Oaxaca" package in R or "Oaxaca" command in STATA (Benmarhnia et al. 2017; Oaxaca 1973; Yannatos et al. 2023b). Only three studies explicitly discussed the assumptions behind their mediation analysis, where Jones et al. and Song et al. mentioned that they assumed no reverse causation between exposure, outcome and mediator, nor unmeasured confounding. Benmarhnia et al. mentioned that they assumed no exposure induced confounder of mediator-outcome relationship. However, none of these studies considered potential interactions between RE and air pollution on the health outcome. Yet, it is possible to consider exposure-mediator(s) interactions in such analyses.

Interpretation of results

Our findings suggest that across different types of studies, 23.1% researchers interpreted or reported coefficients other than the primary exposure of interest (Table 10). However, this pattern varied by study type - exposure disparity studies were more likely to interpret/report additional covariates (32%) compared to EM analysis studies (18.5%) (Table 10). It is important to note here that we did not consider studies that interpreted coefficients of another air pollutant in this analysis.

Table 10 Interpretation of coefficients other than predictors in studies

Interpreted/reported coefficient other than predictor	All studies (N = 134) N (%)[1]	Exposure disparity studies (N = 50) N (%)	EM analysis studies (N = 81) N (%)	Mediation analysis studies (N = 6) N (%)
Yes	22 (16.4%)	16 (32%)	6 (7.4%)	0 (0.0%)
No	112 (83.6%)	34 (68%)	75 (92.6%)	6 (100%)

[1] *Note: Percentages do not sum to 100 due to multiple selections being allowed.*

Nearly all studies included a discussion of RE findings, except for 1.2% of EM analysis studies, when no significant differences were observed across RE. However, the use of conceptual frameworks to justify the inclusion of RE in the study varied by study type. Exposure disparity studies were more likely to employ conceptual frameworks (38.0%) compared to EM analysis studies (19.8%) and mediation studies (33.3%, though this percentage should be interpreted with caution given the small sample size of mediation studies). This pattern suggests that while RE findings are consistently discussed across all study types, exposure disparity researchers more frequently ground their discussions in theoretical frameworks compared to those conducting EM analysis (Table 11).

Table 11 Inclusion of racial/ethnic discussion and conceptual frameworks in studies

Study Characteristics	All studies (N = 134)	Exposure disparity studies (N = 50)	EM analysis studies (N = 81)	Mediation analysis studies (N = 6)
Discussed findings on RE				
No	1 (0.7%)		1 (1.2%)	
Yes	133 (99.3%)	50 (100.0%)	80 (98.8%)	6 (100.0%)
Used a conceptual framework to discuss RE				
Yes	35 (26.1%)	19 (38.0%)	16 (19.8%)	2 (33.3%)
No	99 (73.9%)	31 (62.0%)	65 (80.2%)	4 (66.7%)

Discussion

In this scoping review, we provided an overview of the landscape on air pollution-related studies that utilized RE in California and evaluated the prevalences of some methodological challenges. From 2000 to 2023, we identified a total of 134 publications. Studies exploring air pollution disparity across RE or RE as effect modifiers for air pollution-outcome relationship increased over time, but the number of publications exploring the mediating role of air pollution in outcome disparity across RE remained low. We summarized methodological challenges in such studies and provided corresponding recommendations.

Air pollution estimation-related methodological considerations

In our review, air pollutants were estimated through various approaches, with statistical model, dynamic model and monitoring data alone as the most popular ones. Most of the epidemiological literature documenting the effects of air pollutants on human health (whether considering race/ethnicity or not) is based on a static measurement of air pollutants, assigning exposure at the place of residence. Yet, the concept of activity space has emerged in the past two decades in social epidemiology and has recently been used in air pollution epidemiology (Hoek et al. 2024) indicating that such dynamical exposures can be interesting to further explore especially when assessing health inequities. In a recent study by Letellier et al. (2022), it has been shown that the effect of NO_2 on insulin resistance was higher among Hispanic participants only after considering a dynamical exposure that considers individuals activity space (as opposed to a static exposure considering residential exposure only). It would be important to further explore the importance of considering dynamical exposures when assessing race/ethnic inequalities in regards to air pollution and health effects.

Different geographical resolutions were preferred for different types of study, with more census tract and grid-based estimates in exposure disparity studies and more ZIP Code/ZCTA estimates in effect modification studies. As most health outcomes and population data were collected for varying administrative units (e.g., census tract or ZIP Code), the observed pattern is not surprising. However, administrative boundaries were not the optimal polygons to use in spatial analysis given their irregular shapes and sizes. As exact coordinates of study participants are becoming available in some cohorts, it would be interesting to explore the amplitude of bias introduced by using administrative units such as ZIP Code/ZCTA. In addition, all of the included studies focused on estimating effect estimates considering all spatial units together. Yet, important spatial heterogeneity can occur and implementing spatially varying coefficient models can be interesting to explore to identify areas in which race/ethnic inequalities regarding air pollution and health effects are more (or less) pronounced.

Operationalization and conceptual framework of RE

Our study reveals similar patterns and challenges in the operationalization of RE as those identified by Martinez et al. (2023). Similar to their findings showing most studies did not provide clear RE measurement details (76-81% unclear/not stated), we found that RE categorization schemes often combined race and ethnicity into single constructs without clear theoretical justification. The most common RE categorizations in our sample ("Asian, Black, Hispanic, White" at 20.15% and "Black, White" at 8.96%) mirror the problematic patterns they identified, where authors frequently defaulted to basic demographic categories without addressing the theoretical distinctions between race and ethnicity. This might be related to the effort to achieve large enough sample sizes in each subgroup for statistical inference, but no real inferences can be made for any subgroup without clear theoretical justification. This "ritualistic inclusion" of RE variables, as Martinez et al. term it, manifests in our findings through the prevalent use of broad ethno-racial constructs that may mask important heterogeneity within groups. Moreover, the tendency to treat Hispanic ethnicity as a de facto racial category in many studies (as shown in combinations like "Asian, Black, Hispanic, White") reflects the field's ongoing challenge with properly distinguishing between racial and ethnic classifications. These practices limit our ability to understand how distinct social processes captured by race versus ethnicity may differently influence health outcomes.

There is also a lack of proper conceptualization of RE in air pollution related studies. Only 26.1% of studies included a discussion of conceptual framework for the inclusion of RE, which is even lower in effect modification studies. Casey et al. 2023 found that only 50% of environmental justice research from 2018 to 2021 explicitly used an environmental justice conceptual framework. When restricting to studies published between 2018 and 2021, we still only observed 28.8% of studies using a conceptual framework, indicating that the air pollution field, worse than the overall environmental health research field, needs to further improve our awareness on environmental justice conceptual framework.

Drawing from Payne et al. (2021) and Hicken et al. (2023), a more robust conceptualization of RE in air pollution research must consider several key points. First, we need to move beyond treating race as a simple demographic variable and instead examine it as a marker of exposure to structural racism, which shapes both environmental exposures and vulnerability to their health effects. Hicken et al. emphasize that race categories have different social meanings across locations and time periods, suggesting that researchers should carefully consider local sociopolitical contexts when interpreting racial patterns in air pollution exposures and health outcomes. The inconsistent findings regarding effect modification by race in $PM_{2.5}$-mortality associations likely reflect this complex reality. Additionally, both papers underscore the importance of developing new measures of structural racism specific to environmental health–for example, examining how historical redlining (that only includes 14 cities in California) and current patterns of industrial zoning interact to create racialized patterns of exposure. Rather than simply documenting racial disparities, research should focus on identifying specific discriminatory practices and policies that create and maintain these disparities, ultimately informing more targeted interventions. This requires moving beyond conventional individual-level and demographic covariates to incorporate measures of institutional and systemic racism that may better explain observed racial differences in environmental health outcomes. Emerging literature in social epidemiology has proposed to rely on metrics (Adkins-Jackson et al. 2021) to measure structural racism directly arguing that race/ethnicity may not be ideal as a proxy for racism. Instead, they advocate for using more proximal metrics to capture structural racism including several domains: Political representation, criminal legal system, economic opportunity, and housing. It would be particularly important to explore such metrics when analyzing how structural racisms operates in the context of differential exposure or susceptibility towards air pollution.

Intersectionality of income and RE

As multiple social identities like RE and socioeconomic factors may interact and affect air pollution-related health synergistically, potentially leading to higher vulnerability among people experiencing multiple disadvantaged social identities, it is important to consider intersectionality of income and RE. Explicit consideration of intersectionality between RE and income only existed in 19.6% of studies in our review, with 38.9% for exposure disparity study, 7.4% for effect modification study, and 0% for mediation analysis study. Methods used to consider intersectionality includes adding an interaction term between RE and income and stratified analysis across combinations of RE and income. However, more options exist that could handle such intersectionality, including decomposition analysis (Jackson and VanderWeele 2019) and methods for high dimensional effect modification. Recent approaches based on machine learning algorithms have been proposed to identify and quantify heterogeneity across multiple effect modifiers and their combination. In a recent paper, Cheung et al. (2025) summarize and provide the intuition behind modern ML approaches, including Generalized Random Forests (GRF), Bayesian Additive Regression Trees (BART) or Bayesian Causal Forests (BCF) for effect modification analyses in high-dimensional settings (Cheung et al. 2025). They also provide a case study and statistical code to facilitate the implementation of such techniques in the context of air pollution and health studies considering R/E and the intersection with other socio-economic variables such as income.

Methodological considerations specific to exposure disparity studies

32% of exposure disparity studies interpretated coefficients of variables (e.g., SES) other than RE (see Collins et al. 2022 or Knobel et al. 2023 for example). Such an approach can be seen as misleading. The rationale for adjusting for other variables when conducting descriptive studies is not clear, and some scholars (Lesko et al. 2022) have argued that descriptive studies should not condition or standardize on other variables as one goal of descriptive studies is to describe the world as it is. Standardizing on covariates such as age or gender for example creates a pseudo-population in which R/E subgroups have the same distribution of age and gender which can be seen as misleading. Such practice, that can be referred to as “ritualistic adjustment” has been described (Kaufman 2014) in the social epidemiology literature and is still prevalent in the studies we identified in this review.

Methodological considerations specific to effect modification studies

The distinguishment between interaction and effect modification also needs to be emphasized, especially their epidemiological interpretations. As defined by VanderWeele, an interaction "requires the effect of two exposures together to be different from the combination of the two effects considered separately", while effect modification "is defined in terms of the effect of one intervention [exposure] varying across strata of a second variable [effect modifier]" (VanderWeele 2009). An important distinguishment between interaction and effect modification is, confounding between exposure and outcome needs to be accounted for when evaluating interaction, while confounding between effect modifier and outcome is considered part of the effect modification and does not need to be accounted for (VanderWeele 2009). Unfortunately, interaction is also a widely used statistical term and people tend to use it without considering their epidemiological interpretation. 20.9% of the effect modification studies in our review only described their effect modification analysis using terms like interaction or stratification, likely referring to the analytical methods, while explicitly describing their analysis as evaluating effect modification or effect heterogeneity will help clarify the actual purpose of their analyses. On the other hand, 6.2% of the studies discussed residual confounding on their effect modifiers, while such confounding should be considered as part of the effect modification. Besides, 2.5% of studies (Bell and Dominici 2008; Tong et al. 2022) included multiple effect modifiers in the second stage of the Bayesian hierarchical model, attempting to "adjusting for other effect modifiers when evaluating the effect modification", which is not aligned with the definition of effect modification. As opposed to causal interaction, no manipulation is targeted for effect modifiers and the concept of bias does not apply here.

Another important aspect for reporting effect modification is conducting formal heterogeneity test like Cochran's Q test, Wald test, or conducting regression analysis using interaction terms, to evaluate whether the effects are truly different across RE strata (Kaufman and MacLehose 2013; Ward et al. 2019). However, only 69.1% of effect modification studies in our review conducted a formal heterogeneity test and about half of the studies without a formal heterogeneity test still reported stratum-specific effect estimates. This proportion is consistent over the three periods (2000-2010, 2011-2019, and 2020-2024). The prevalence of conducting formal heterogeneity tests is higher than the 34% identified in epidemiological studies of disparities in toxic chemical exposure and neurodevelopmental outcomes by Payne-Sturges et al. We would like to encourage the use of formal heterogeneity test and the report of stratum specific results when heterogeneity is detected.

In population-based research, presenting and interpreting coefficients of covariates other than the exposure of interest from a multivariable model, such as confounders, leads to a scenario called "table-2 fallacy" (Westreich and Greenland 2013). Interpreting coefficients of covariates other than the exposure of interest is problematic because the set of confounders that need to be adjusted for to obtain a causal relationship with the outcome is likely different for the exposure of interest and the covariate whose coefficient is being interpreted. This might not apply when multiple air pollutants were considered as confounders of each other and included in the same multivariate model (e.g., multiple-pollutant models) as many air pollutants share the same confounders for health outcomes, thus we excluded such studies in the discussion of table-2 fallacy and discussed multiple pollutants in the next paragraph. The prevalence of table-2 fallacy is relatively low in studies included in our review, with only 7.4% of studies interpreted coefficients of non-air pollutant variable (An and Xiang 2015; De Grubb et al. 2017; Jorgenson et al. 2020; Payne-Sturges et al. 2022). Recommendations regarding how to avoid the table-2 fallacy have been described elsewhere (Benmarhnia et al. 2021).

Studies evaluated the health effects of multiple pollutants with different methods in our review: conducting separate analysis for each pollutant using single-pollutant models (see Neophytou et al. 2016 for example), conducting separate analysis for each pollutant while including other air pollutants as confounders (e.g., including $PM_{2.5}$ total mass as a confounder when evaluating the effect of $PM_{2.5}$ constituents), conducting one analysis by including all pollutants in the same multiple-pollutant models and interpreting the coefficients of all air pollutants from the same model (see Enders et al. 2019 or Di et al. 2017 as examples), and employing mixture methods to explore the effect of changing all pollutant levels simultaneous (e.g., quantile g-computation) (see Xu et al. 2020 or Sun et al. 2022).

Methodological considerations specific to mediation analysis studies

While we identified fewer studies that considered a mediation framework, we argue that such approaches can be particularly helpful at quantifying how much inequalities across R/E subgroups in relation to a given health outcome are due to air pollution. The use of mediation techniques to analyze the drivers of SES inequalities in health is receiving increasing attention (Jackson 2021). Indeed, as the use of R/E as the main exposure of interest has been criticized due to the violation of the consistency assumption and the lack of manipulability (VanderWeele 2018), some scholars have proposed to shift the manipulability criteria towards the mediator, such as a given air pollutant. In this context, it has been highlighted that it would be more accurate to focus on a decomposition framework rather than a causal mediation one. Indeed, when estimating a natural indirect effect for example, it requires a hypothetical manipulation of the exposure, while a decomposition only requires a change in the distribution of the mediator(s). Recent decomposition techniques for such setting have been proposed (Smith et al. 2024) and we argue that it would be particularly interesting to implement such techniques to multiple air pollutants, health outcomes in California and elsewhere.

Table 12 List of selected methodological recommendations.

Methodological considerations	Recommendations
Air pollution estimation	1. Explore dynamic exposure considering activity space 2. Consider grid cells instead of administrative units as the spatial unit of analysis 3. Explore spatial heterogeneity of air pollution-health association
Operationalization and conceptual framework of race and ethnicity (RE)	1. Provide theoretical justifications for the RE categorization and avoid categorizations that are too coarse 2. Provide conceptual frameworks on the role of RE in air pollution-related studies 3. Consider RE as a marker of exposure to structural racism 4. Utilize metrics that captures structural racism in different domains
Intersectionality of income and RE	1. Evaluate intersectionality using emerging methods like decomposition analysis and machine-learning based algorithms for high-dimensional heterogeneity.
Exposure disparity studies	1. Avoid adjusting/standardizing for other variables when conducting descriptive studies
Effect modification studies	1. Distinguish between interaction and effect modification, especially its implications for confounding adjustment 2. Conduct formal heterogeneity test when using stratified analyses. 3. Avoid interpreting coefficients of covariates other than the exposure of interest (table-2 fallacy)
Mediation analysis studies	1. More utilization is encouraged 2. Clarify the hypothetical interventions of interest (or lack of thereof) and adopt relevant mediation or decomposition frameworks accordingly. 3. Consider analytical approaches that consider multiple mediators that are dependent with each other

Limitations

There are some limitations in this review. First, we focused on the methodological choices and assumptions behind air pollution-related studies that utilized RE and did not provide summaries of observed disparity across racial and ethnic groups. However, previous reviews already provided detailed summaries of disparity on the associations of air pollution and pregnancy outcome (Dzekem et al. 2024), PM and birth outcomes (Heo et al. 2019; Thayamballi et al. 2021), and ozone and mortality or hospital admission (Bell et al. 2014). Second, we did not exhaust all methodological considerations in air pollution-related health studies that used RE, but this review should provide a good start for discussion. Third, we restricted our review to six criteria air pollutants, air quality index, and wildfire smoke to restrict the review to a manageable size and disregarded other air pollutants. However, the methodological challenges and recommendations discussed in this review should apply to other air pollutants. Fourth, we only considered income as a representation of material resources aspect of socioeconomic status.

Conclusions

In this comprehensive scoping review, we synthetized the evolving landscape of air pollution-related health studies in California that incorporate racial/ethnic considerations. Our analysis, including studies from 2000 to 2023, revealed a growing trend in research exploring air pollution disparities across RE groups and examining RE as effect modifiers in air pollution-outcome relationships. However, studies investigating the mediating role of air pollution in outcome disparities across RE remain underrepresented. Through our systematic approach, we have not only mapped the current state of research but also identified key methodological challenges and provided targeted recommendations for researchers. This work serves a double purpose: guiding future research endeavors and equipping policymakers and the public with a nuanced understanding of the conceptual frameworks and assumptions underlying these studies. By addressing these critical aspects, we aim to enhance the quality and impact of air pollution-related health research, ultimately contributing to more equitable and effective public health strategies in California and beyond.

Bibliography

Adkins-Jackson PB, Chantarat T, Bailey ZD, Ponce NA. 2021. Measuring Structural Racism: A Guide for Epidemiologists and Other Health Researchers. Am J Epidemiol 191:539–547; doi:10.1093/aje/kwab239.

An R, Xiang X. 2015. Ambient fine particulate matter air pollution and leisure-time physical inactivity among US adults. Public Health 129:1637–1644; doi:10.1016/j.puhe.2015.07.017.

Bailey ZD, Krieger N, Agénor M, Graves J, Linos N, Bassett MT. 2017. Structural racism and health inequities in the USA: evidence and interventions. The Lancet 389:1453–1463; doi:10.1016/S0140-6736(17)30569-X.

Baron RM, Kenny DA. 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Pers Soc Psychol 51:1173–1182; doi:10.1037//0022-3514.51.6.1173.

Bell ML, Dominici F. 2008. Effect Modification by Community Characteristics on the Short-term Effects of Ozone Exposure and Mortality in 98 US Communities. Am J Epidemiol 167:986–997; doi:10.1093/aje/kwm396.

Bell ML, Zanobetti A, Dominici F. 2014. Who is More Affected by Ozone Pollution? A Systematic Review and Meta-Analysis. Am J Epidemiol 180:15–28; doi:10.1093/aje/kwu115.

Benmarhnia T, Hajat A, Kaufman JS. 2021. Inferential challenges when assessing racial/ethnic health disparities in environmental research. Environ Health 20:7; doi:10.1186/s12940-020-00689-5.

Benmarhnia T, Huang J, Basu R, Wu J, Bruckner TA. 2017. Decomposition Analysis of Black–White Disparities in Birth Outcomes: The Relative Contribution of Air Pollution and Social Factors in California. Environ Health Perspect 125:107003; doi:10.1289/EHP490.

Burke M, Childs ML, de la Cuesta B, Qiu M, Li J, Gould CF, et al. 2023. The contribution of wildfire to PM2.5 trends in the USA. Nature 622:761–766; doi:10.1038/s41586-023-06522-6.

California's Population. Public Policy Institute of California. Available: https://www.ppic.org/publication/californias-population/ [accessed 12 November 2024].

Casey JA, Daouda M, Babadi RS, Do V, Flores NM, Berzansky I, et al. 2023. Methods in Public Health Environmental Justice Research: a Scoping Review from 2018 to 2021. Curr Envir Health Rpt; doi:10.1007/s40572-023-00406-7.

Chen J, Hoek G. 2020. Long-term exposure to PM and all-cause and cause-specific mortality: A systematic review and meta-analysis. Environment International 143:105974; doi:10.1016/j.envint.2020.105974.

Cheung M, Dimitrova A, Benmarhnia T. 2025. An overview of modern machine learning methods for effect measure modification analyses in high-dimensional settings. SSM - Population Health 29:101764; doi:10.1016/j.ssmph.2025.101764.

Chin MT. 2015. Basic mechanisms for adverse cardiovascular events associated with air pollution. Heart 101:253–256; doi:10.1136/heartjnl-2014-306379.

Collins TW, Grineski SE, Nadybal SM. 2022. A Comparative Approach for Environmental Justice Analysis: Explaining Divergent Societal Distributions of Particulate Matter and Ozone Pollution across U.S. Neighborhoods. Annals of the American Association of Geographers 112:522–541; doi:10.1080/24694452.2021.1935690.

De Grubb MCM, Kilbourne B, Kilbourne K, Langston M, Gittner L, Zoorob RJ, et al. 2017. Socioeconomic, environmental, and geographic factors and US lung cancer mortality, 1999-2009. family med commun hlth 5:3–12; doi:10.15212/FMCH.2017.0108.

Di Q, Wang Y, Zanobetti A, Wang Y, Koutrakis P, Choirat C, et al. 2017. Air Pollution and Mortality in the Medicare Population. N Engl J Med 376:2513–2522; doi:10.1056/NEJMoa1702747.

Dzekem BS, Aschebrook-Kilfoy B, Olopade CO. 2024. Air Pollution and Racial Disparities in Pregnancy Outcomes in the United States: A Systematic Review. J Racial Ethn Health Disparities 11:535–544; doi:10.1007/s40615-023-01539-z.

Enders C, Pearson D, Harley K, Ebisu K. 2019. Exposure to coarse particulate matter during gestation and term low birthweight in California: Variation in exposure and risk across region and socioeconomic subgroup. Science of The Total Environment 653:1435–1444; doi:10.1016/j.scitotenv.2018.10.323.

Environmental Justice. 2011. State of California - Department of Justice - Office of the Attorney General. Available: https://oag.ca.gov/environment/justice [accessed 19 March 2025].

EPA U. Green Book | US EPA. Available: https://www3.epa.gov/airquality/greenbook/kbtc.html [accessed 12 November 2024a].

EPA U. Green Book | US EPA. Available: https://www3.epa.gov/airquality/greenbook/jbtc.html [accessed 12 November 2024b].

Eum K-D, Honda TJ, Wang B, Kazemiparkouhi F, Manjourides J, Pun VC, et al. 2022. Long-term nitrogen dioxide exposure and cause-specific mortality in the U.S. Medicare population. Environmental Research 207:112154; doi:10.1016/j.envres.2021.112154.

Ford B, Val Martin M, Zelasky SE, Fischer EV, Anenberg SC, Heald CL, et al. 2018. Future Fire Impacts on Smoke Concentrations, Visibility, and Health in the Contiguous United States. Geohealth 2:229–247; doi:10.1029/2018GH000144.

Gee GC, Payne-Sturges DC. 2004. Environmental Health Disparities: A Framework Integrating Psychosocial and Environmental Concepts. Environmental Health Perspectives 112:1645; doi:10.1289/ehp.7074.

Gharibi H, Entwistle MR, Ha S, Gonzalez M, Brown P, Schweizer D, et al. 2019. Ozone pollution and asthma emergency department visits in the Central Valley, California, USA, during June to September of 2015: a time-stratified case-crossover analysis. Journal of Asthma 56:1037–1048; doi:10.1080/02770903.2018.1523930.

Hajat A, MacLehose RF, Rosofsky A, Walker KD, Clougherty JE. 2021. Confounding by Socioeconomic Status in Epidemiological Studies of Air Pollution and Health: Challenges and Opportunities. Environ Health Perspect 129:65001; doi:10.1289/EHP7980.

Heo S, Fong KC, Bell ML. 2019. Risk of particulate matter on birth outcomes in relation to maternal socio-economic factors: a systematic review. Environ Res Lett 14:123004; doi:10.1088/1748-9326/ab4cd0.

Hicken MT, Adar SD, Hajat A, Kershaw KN, Do DP, Barr RG, et al. 2016. Air Pollution, Cardiovascular Outcomes, and Social Disadvantage: The Multi-ethnic Study of Atherosclerosis. Epidemiology 27:42–50; doi:10.1097/EDE.0000000000000367.

Hicken MT, Payne-Sturges D, McCoy E. 2023. Evaluating Race in Air Pollution and Health Research: Race, PM2.5 Air Pollution Exposure, and Mortality as a Case Study. Curr Envir Health Rpt 10:1–11; doi:10.1007/s40572-023-00390-y.

Hoek, G., Vienneau, D. and de Hoogh, K., 2024. Does residential address-based exposure assessment for outdoor air pollution lead to bias in epidemiological studies?. Environmental Health, 23(1), p.75.

House TW. 2021. Executive Order on Tackling the Climate Crisis at Home and Abroad. The White House. Available: https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/27/executive-order-on-tackling-the-climate-crisis-at-home-and-abroad/ [accessed 3 November 2024].

Huangfu P, Atkinson R. 2020. Long-term exposure to NO2 and O3 and all-cause and respiratory mortality: A systematic review and meta-analysis. Environment International 144:105998; doi:10.1016/j.envint.2020.105998.

Jackson JW. 2021. Meaningful Causal Decompositions in Health Equity Research: Definition, Identification, and Estimation Through a Weighting Framework. Epidemiology 32:282–290; doi:10.1097/EDE.0000000000001319.

Jackson JW, VanderWeele TJ. 2019. Intersectional decomposition analysis with differential exposure, effects, and construct. Soc Sci Med 226:254–259; doi:10.1016/j.socscimed.2019.01.033.

Jbaily A, Zhou X, Liu J, Lee T-H, Kamareddine L, Verguet S, et al. 2022. Air pollution exposure disparities across US population and income groups. Nature 601:228–233; doi:10.1038/s41586-021-04190-y.

Jin T, Di Q, Réquia WJ, Danesh Yazdi M, Castro E, Ma T, et al. 2022. Associations between long-term air pollution exposure and the incidence of cardiovascular diseases among American older adults. Environment International 170:107594; doi:10.1016/j.envint.2022.107594.

Jones CP. 2000. Levels of racism: a theoretic framework and a gardener's tale. American Journal of Public Health 90:1212; doi:10.2105/ajph.90.8.1212.

Jones MR, Diez-Roux AV, O'Neill MS, Guallar E, Sharrett AR, Post W, et al. 2015. Ambient air pollution and racial/ethnic differences in carotid intima-media thickness in the Multi-Ethnic Study of Atherosclerosis (MESA). J Epidemiol Community Health 69: 1191–1198.

Jorgenson AK, Hill TD, Clark B, Thombs RP, Ore P, Balistreri KS, et al. 2020. Power, proximity, and physiology: does income inequality and racial composition amplify the impacts of air pollution on life expectancy in the United States? Environ Res Lett 15:024013; doi:10.1088/1748-9326/ab6789.

Karmel PE, FitzGibbon TN. PM2.5: Federal and California Regulation of Fine Particulate Air Pollution.

Kaufman JS. 2014. Commentary: Race: Ritual, Regression, and Reality. Epidemiology 25:485; doi:10.1097/EDE.0000000000000117.

Kaufman JS, MacLehose RF. 2013. Which of These Things is Not Like the Others? Cancer 119:4216–4222; doi:10.1002/cncr.28359.

Kelly JT, Jang C, Timin B, Di Q, Schwartz J, Liu Y, et al. 2021. Examining PM2.5 concentrations and exposure using multiple models. Environmental Research 196:110432; doi:10.1016/j.envres.2020.110432.

Knobel P, Hwang I, Castro E, Sheffield P, Holaday L, Shi L, et al. 2023. Socioeconomic and racial disparities in source-apportioned PM2.5 levels across urban areas in the contiguous US, 2010. Atmospheric Environment 303:119753; doi:10.1016/j.atmosenv.2023.119753.

Kulick ER, Kaufman JD, Sack C. 2023. Ambient Air Pollution and Stroke: An Updated Review. Stroke 54:882–893; doi:10.1161/STROKEAHA.122.035498.

Lee H, Cashin AG, Lamb SE, Hopewell S, Vansteelandt S, VanderWeele TJ, et al. 2021. A Guideline for Reporting Mediation Analyses of Randomized Trials and Observational Studies: The AGReMA Statement. JAMA 326:1045–1056; doi:10.1001/jama.2021.14075.

Lee KK, Spath N, Miller MR, Mills NL, Shah ASV. 2020. Short-term exposure to carbon monoxide and myocardial infarction: A systematic review and meta-analysis. Environment International 143:105901; doi:10.1016/j.envint.2020.105901.

Lesko, C.R., Fox, M.P. and Edwards, J.K., 2022. A framework for descriptive epidemiology. American journal of epidemiology, 191(12), pp.2063-2070.

Letellier N, Zamora S, Spoon C, Yang J-A, Mortamais M, Escobar GC, et al. 2022. Air pollution and metabolic disorders: Dynamic versus static measures of exposure among Hispanics/Latinos and non-Hispanics. Environmental Research 209:112846; doi:10.1016/j.envres.2022.112846.

Liu J, Clark LP, Bechle MJ, Hajat A, Kim S-Y, Robinson AL, et al. 2021. Disparities in air pollution exposure in the United States by race/ethnicity and income, 1990–2010. Environmental health perspectives 129: 127005.

Lurmann F, Avol E, Gilliland F. 2015. Emissions reduction policies and recent trends in Southern California's ambient air quality. Journal of the Air & Waste Management Association 65:324–335; doi:10.1080/10962247.2014.991856.

Martinez RAM, Andrabi N, Goodwin AN, Wilbur RE, Smith NR, Zivich PN. 2023. Conceptualization, Operationalization, and Utilization of Race and Ethnicity in Major Epidemiology Journals, 1995-2018: A Systematic Review. Am J Epidemiol 192:483–496; doi:10.1093/aje/kwac146.

Mohai P, Pellow D, Roberts JT. 2009. Environmental Justice. Annu Rev Environ Resour 34:405–430; doi:10.1146/annurev-environ-082508-094348.

Morello-Frosch R, Lopez R. 2006. The riskscape and the color line: Examining the role of segregation in environmental health disparities. Environmental Research 102:181–196; doi:10.1016/j.envres.2006.05.007.

Murray CJL, Aravkin AY, Zheng P, Abbafati C, Abbas KM, Abbasi-Kangevari M, et al. 2020. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. The Lancet 396:1223–1249; doi:10.1016/S0140-6736(20)30752-2.

Neophytou AM, White MJ, Oh SS, Thakur N, Galanter JM, Nishimura KK, et al. 2016. Air Pollution and Lung Function in Minority Youth with Asthma in the GALA II (Genes–Environments and Admixture in Latino Americans) and SAGE II (Study of African Americans, Asthma, Genes, and Environments) Studies. Am J Respir Crit Care Med 193:1271–1280; doi:10.1164/rccm.201508-1706OC.

Oaxaca R. 1973. Male-Female Wage Differentials in Urban Labor Markets. International Economic Review 14:693–709; doi:10.2307/2525981.

Orellano P, Reynoso J, Quaranta N. 2021. Short-term exposure to sulphur dioxide (SO2) and all-cause and respiratory mortality: A systematic review and meta-analysis. Environment International 150:106434; doi:10.1016/j.envint.2021.106434.

Orellano P, Reynoso J, Quaranta N, Bardach A, Ciapponi A. 2020. Short-term exposure to particulate matter (PM10 and PM2.5), nitrogen dioxide (NO2), and ozone (O3) and all-cause and cause-specific mortality: Systematic review and meta-analysis. Environment International 142:105876; doi:10.1016/j.envint.2020.105876.

Payne -Sturges Devon C., Gee GC, Cory -Slechta Deborah A. 2021. Confronting Racism in Environmental Health Sciences: Moving the Science Forward for Eliminating Racial Inequities. Environmental Health Perspectives 129:055002; doi:10.1289/EHP8186.

Payne-Sturges DC, Puett R, Cory-Slechta DA. 2022. Both parents matter: a national-scale analysis of parental race/ethnicity, disparities in prenatal PM2.5 exposures and related impacts on birth outcomes. Environmental Health 21:47; doi:10.1186/s12940-022-00856-w.

Payne-Sturges DC, Taiwo TK, Ellickson K, Mullen H, Tchangalova N, Anderko L, et al. 2023. Disparities in Toxic Chemical Exposures and Associated Neurodevelopmental Outcomes: A Scoping Review and Systematic Evidence Map of the Epidemiological Literature. Environmental Health Perspectives 131:096001; doi:10.1289/EHP11750.

Perry MJ, Arrington S, Freisthler MS, Ibe IN, McCray NL, Neumann LM, et al. 2021. Pervasive structural racism in environmental epidemiology. Environmental Health 20:119; doi:10.1186/s12940-021-00801-3.

Smith MJ, McClure LA, Long DL. 2024. Path-specific causal decomposition analysis with multiple correlated mediator variables. Statistics in Medicine n/a; doi:10.1002/sim.10182.

Song L, Smith GS, Adar SD, Post WS, Guallar E, Navas-Acien A, et al. 2020a. Ambient air pollution as a mediator in the pathway linking race/ethnicity to blood pressure elevation: The multi-ethnic study of atherosclerosis (MESA). Environmental Research 180:108776; doi:10.1016/j.envres.2019.108776.

Song L, Smith GS, Adar SD, Post WS, Guallar E, Navas-Acien A, et al. 2020b. Ambient air pollution as a mediator in the pathway linking race/ethnicity to blood pressure elevation: The multi-ethnic study of atherosclerosis (MESA). Environmental Research 180:108776; doi:10.1016/j.envres.2019.108776.

Spiller E, Proville J, Roy A, Muller NZ. 2021. Mortality Risk from PM2.5: A Comparison of Modeling Approaches to Identify Disparities across Racial/Ethnic Groups in Policy Outcomes. Environmental Health Perspectives 129:127004; doi:10.1289/EHP9001.

Stanek LW, Brown JS, Stanek J, Gift J, Costa DL. 2011. Air pollution toxicology—a brief review of the role of the science in shaping the current understanding of air pollution health risks. Toxicol Sci 120:S8–S27; doi:10.1093/toxsci/kfq367.

Sun Y, Li X, Benmarhnia T, Chen J-C, Avila C, Sacks DA, et al. 2022. Exposure to air pollutant mixture and gestational diabetes mellitus in Southern California: Results from electronic health record data of a large pregnancy cohort. Environment International 158:106888; doi:10.1016/j.envint.2021.106888.

Swilley-Martinez ME, Coles SA, Miller VE, Alam IZ, Fitch KV, Cruz TH, et al. 2023. "We adjusted for race" now what: A systematic review of utilization and reporting of race in AJE and Epidemiology, 2020-2021. Epidemiologic Reviews mxad010; doi:10.1093/epirev/mxad010.

Thayamballi N, Habiba S, Laribi O, Ebisu K. 2021. Impact of Maternal Demographic and Socioeconomic Factors on the Association Between Particulate Matter and Adverse Birth Outcomes: a Systematic Review and Meta-analysis. J Racial and Ethnic Health Disparities 8:743–755; doi:10.1007/s40615-020-00835-2.

Tong M, Li P, Wang M, Sun Y, Han Y, Liu H, et al. 2022. Time-varying association between fetal death and gestational exposure to ambient fine particles: a nationwide epidemiological study of 49 million fetuses in the contiguous US from 1989 to 2004. International Journal of Epidemiology 51:1984–1999; doi:10.1093/ije/dyac103.

Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. 2018. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Ann Intern Med 169:467–473; doi:10.7326/M18-0850.

U.S. EPA and WHO partner to protect public health. Available: https://www.who.int/news/item/20-01-2022-u.s.-epa-and-world-health-organization-partner-to-protect-public-health [accessed 3 November 2024].

US EPA O. 2014. Criteria Air Pollutants. Available: https://www.epa.gov/criteria-air-pollutants [accessed 2 October 2024].

US EPA O. 2015. Learn About Environmental Justice. Available: https://www.epa.gov/environmentaljustice/learn-about-environmental-justice [accessed 3 November 2024].

VanderWeele TJ. 2016. Mediation Analysis: A Practitioner's Guide. Annual Review of Public Health 37:17–32; doi:10.1146/annurev-publhealth-032315-021402.

VanderWeele TJ. 2009. On the Distinction Between Interaction and Effect Modification. Epidemiology 20:863–871; doi:10.1097/EDE.0b013e3181ba333c.

VanderWeele TJ, Robinson WR. 2014. On the Causal Interpretation of Race in Regressions Adjusting for Confounding and Mediating Variables: Epidemiology 25:473–484; doi:10.1097/EDE.0000000000000105.

VanderWeele TJ. 2018.On well-defined hypothetical interventions in the potential outcomes framework. Epidemiology 29(4):e24–25

Ward JB, Gartner DR, Keyes KM, Fliss MD, McClure ES, Robinson WR. 2019. How do we assess a racial disparity in health? Distribution, interaction, and interpretation in epidemiological studies. Annals of Epidemiology 29:1–7; doi:10.1016/j.annepidem.2018.09.007.

Westreich D, Greenland S. 2013. The Table 2 Fallacy: Presenting and Interpreting Confounder and Modifier Coefficients. Am J Epidemiol 177:292–298; doi:10.1093/aje/kws412.

Woodruff TJ, Parker JD, Kyle AD, Schoendorf KC. 2003a. Disparities in exposure to air pollution during pregnancy. Environmental Health Perspectives 111:942–946; doi:10.1289/ehp.5317.

Woodruff TJ, Parker JD, Kyle AD, Schoendorf KC. 2003b. Disparities in exposure to air pollution during pregnancy. Environmental Health Perspectives 111:942–946; doi:10.1289/ehp.5317.

Xu J, White AJ, Niehoff NM, O'Brien KM, Sandler DP. 2020. Airborne metals exposure and risk of hypertension in the Sister Study. Environmental Research 191:110144; doi:10.1016/j.envres.2020.110144.

Yannatos I, Stites S, Brown RT, McMillan CT. 2023a. Contributions of neighborhood social environment and air pollution exposure to Black-White disparities in epigenetic aging. PLOS ONE 18:e0287112; doi:10.1371/journal.pone.0287112.

Yannatos I, Stites S, Brown RT, McMillan CT. 2023b. Contributions of neighborhood social environment and air pollution exposure to Black-White disparities in epigenetic aging. PLOS ONE 18:e0287112; doi:10.1371/journal.pone.0287112.

Younan D, Wang X, Gruenewald T, Gatz M, Serre ML, Vizuete W, et al. 2022a. Racial/Ethnic Disparities in Alzheimer's Disease Risk: Role of Exposure to Ambient Fine Particles. The Journals of Gerontology: Series A 77:977–985; doi:10.1093/gerona/glab231.

Younan D, Wang X, Gruenewald T, Gatz M, Serre ML, Vizuete W, et al. 2022b. Racial/Ethnic Disparities in Alzheimer's Disease Risk: Role of Exposure to Ambient Fine Particles. The Journals of Gerontology: Series A 77:977–985; doi:10.1093/gerona/glab231.

Zheng X, Orellano P, Lin H, Jiang M, Guan W. 2021. Short-term exposure to ozone, nitrogen dioxide, and sulphur dioxide and emergency department visits and hospital admissions due to asthma: A systematic review and meta-analysis. Environment International 150:106435; doi:10.1016/j.envint.2021.106435.

Supplementary materials

Supplementary Table 1 Search terms used for different databases for original articles

Database	Search Terms
PubMed	("atmospheric pollutant"[tiab] OR "atmospheric pollutants"[tiab] OR "atmospheric pollution"[tiab] OR "air pollution"[tiab] OR "air pollutant"[tiab] OR "air pollutants"[tiab] OR "air quality"[tiab] OR "wildfire"[tiab] OR "particulate matter"[tiab] OR "PM"[tiab] OR "PM2.5"[tiab] OR "PM10"[tiab] OR "ozone"[tiab] OR "O3"[tiab] OR "carbon monoxide"[tiab] OR ("Lead"[tiab] AND "air"[tiab]) OR "sulfur dioxide"[tiab] OR "SO2"[tiab] OR "nitrogen dioxide"[tiab] OR "NO2"[tiab]) AND ("race"[tiab] OR "ethnicity"[tiab] OR "racial"[tiab] OR "ethnic"[tiab] OR "races"[tiab] OR "ethnicities"[tiab] OR "minority group"[tiab] OR "minority groups"[tiab]) AND ("US" OR "United States" OR "California" OR "USA" OR "America" OR "American") AND (English[Language]) NOT (Letter[Publication Type]) NOT (Comment[Publication Type]) NOT (Editorial[Publication Type]) NOT (Review[Publication Type]) NOT (News[Publication Type]) NOT (Case Reports[Publication Type])
EMBASE	('atmospheric pollut*':ab,ti OR 'air pollut*':ab,ti OR 'air quality':ab,ti OR 'wildfire':ab,ti OR 'particulate matter':ab,ti OR 'pm':ab,ti OR 'pm2.5':ab,ti OR 'pm10':ab,ti OR 'ozone':ab,ti OR 'o3':ab,ti OR 'carbon monoxide':ab,ti OR ('lead':ab,ti AND 'air':ab,ti) OR 'sulfur dioxide':ab,ti OR 'so2':ab,ti OR 'nitrogen dioxide':ab,ti OR 'no2':ab,ti) AND ("race$":ab,ti OR 'ethnicit*':ab,ti OR 'racial':ab,ti OR 'ethinic':ab,ti OR "minority group$":ab,ti) AND ('us' OR 'united states'/exp OR 'united states' OR 'california'/exp OR 'california' OR 'usa'/exp OR 'usa' OR 'america'/exp OR 'america' OR 'american'/exp OR 'american') AND ([article]/lim OR [article in press]/lim) AND [english]/lim AND [01-01-2000]/sd NOT [01-01-2024]/sd
Web of Science	((TI = ("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR ("Lead" AND "air") OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2")) OR (AB = ("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR ("Lead" AND "air") OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2"))) AND ((TI = ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups")) OR (AB = ("race" OR "racial" OR

	"ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups"))) AND (CU = ("US" OR "United States" OR "California" OR "USA" OR "America" OR "American")) AND (LA = English) NOT DT=(Letter OR Comment OR Editorial Material OR Review OR News Item OR Case Reports)
CINHAL	(TI (("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR "lead" AND "air" OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2") AND ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups") AND ("united states" OR "california" OR "usa" OR "america" OR "american")) OR AB (("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR "lead" AND "air" OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2") AND ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups") AND ("united states" OR "california" OR "usa" OR "america" OR "american"))) NOT PT (Letter OR Comment OR Editorial OR Review OR news OR case reports)

Supplementary Table 2 Search terms used for different databases for review articles

Database	**Search Terms**
PubMed	("atmospheric pollutant"[tiab] OR "atmospheric pollutants"[tiab] OR "atmospheric pollution"[tiab] OR "air pollution"[tiab] OR "air pollutant"[tiab] OR "air pollutants"[tiab] OR "air quality"[tiab] OR "wildfire"[tiab] OR "particulate matter"[tiab] OR "PM"[tiab] OR "PM2.5"[tiab] OR "PM10"[tiab] OR "ozone"[tiab] OR "O3"[tiab] OR "carbon monoxide"[tiab] OR ("Lead"[tiab] AND "air"[tiab]) OR "sulfur dioxide"[tiab] OR "SO2"[tiab] OR "nitrogen dioxide"[tiab] OR "NO2"[tiab]) AND ("race"[tiab] OR "ethnicity"[tiab] OR "racial"[tiab] OR "ethnic"[tiab] OR "races"[tiab] OR "ethnicities"[tiab] OR "minority group"[tiab] OR "minority groups"[tiab]) AND ("US" OR "United States" OR "California" OR "USA" OR "America" OR "American") AND (English[Language]) AND (Review[Publication Type]) NOT (Letter[Publication Type]) NOT (Comment[Publication Type]) NOT (Editorial[Publication Type]) NOT (News[Publication Type]) NOT (Case Reports[Publication Type])
EMBASE	('atmospheric pollut*':ab,ti OR 'air pollut*':ab,ti OR 'air quality':ab,ti OR 'wildfire':ab,ti OR 'particulate matter':ab,ti OR 'pm':ab,ti OR 'pm2.5':ab,ti

	OR 'pm10':ab,ti OR 'ozone':ab,ti OR 'o3':ab,ti OR 'carbon monoxide':ab,ti OR ('lead':ab,ti AND 'air':ab,ti) OR 'sulfur dioxide':ab,ti OR 'so2':ab,ti OR 'nitrogen dioxide':ab,ti OR 'no2':ab,ti) AND ("race$":ab,ti OR 'ethnicit*':ab,ti OR 'racial':ab,ti OR 'ethinic':ab,ti OR "minority group$":ab,ti) AND ('us' OR 'united states'/exp OR 'united states' OR 'california'/exp OR 'california' OR 'usa'/exp OR 'usa' OR 'america'/exp OR 'america' OR 'american'/exp OR 'american') AND [english]/lim AND [01-01-2000]/sd NOT [01-01-2024]/sd AND ([letter]/lim OR [review]/lim)
Web of Science	((TI = ("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR ("Lead" AND "air") OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2")) OR (AB = ("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR ("Lead" AND "air") OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2"))) AND ((TI = ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups")) OR (AB = ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups"))) AND (CU = ("US" OR "United States" OR "California" OR "USA" OR "America" OR "American")) AND (LA = English) AND DT = (Review) NOT DT=(Letter OR Comment OR Editorial Material OR News Item OR Case Reports)
CINHAL	(TI (("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR "lead" AND "air" OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2") AND ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups") AND ("united states" OR "california" OR "usa" OR "america" OR "american")) OR AB (("atmospheric pollutant" OR "atmospheric pollutants" OR "atmospheric pollution" OR "air pollution" OR "air pollutant" OR "air pollutants" OR "air quality" OR "wildfire" OR "particulate matter" OR "PM" OR "PM2.5" OR "PM10" OR "ozone" OR "O3" OR "carbon monoxide" OR "lead" AND "air" OR "sulfur dioxide" OR "SO2" OR "nitrogen dioxide" OR "NO2") AND ("race" OR "racial" OR "ethnicity" OR "ethnic" OR "races" OR "ethnicities" OR "minority group" OR "minority groups") AND ("united states" OR "california" OR "usa" OR "america" OR "american")))

Supplementary Table 3 CARB Reports included to identify original articles

Sl.	Project Title	Contract Number	Principal Investigator
1.	Updating and Completing the Environmental Justice Screening Method	11-336	Sadd, James; Manuel Pastor; and Rachel Morello-Frosch
2.	Risk of pediatric asthma morbidity from multipollutant exposures	10-319	Delfino, Ralph; Kleeman, Michael; Gillen, Dan; Wu, Jun; Nickerson, Bruce
3.	Is disparity in asthma among Californians due to higher pollutant exposures, greater susceptibility, or both?	07-309	Meng, Ying-Ying
4.	Air Pollution and Environmental Justice: Integrating Indicators of Cumulative Impact and Socio-Economic Vulnerability into Regulatory Decision-Making	04-308	Pastor, Manuel; Morello-Frosch, Rachel; Sadd, James

Supplementary Table 4 List of 134 studies extracted and the corresponding study type

(see Excel file)

Supplementary Table 5 Frequency of air-pollutants used across study type

Air Pollutants used in studies	All studies (N = 134) N (%)[1]	Exposure disparity studies (N = 50) N (%)	EM analysis studies (N = 81) N (%)	Mediation analysis studies (N = 6) N (%)
PM2.5	100 (74.6%)	32 (64%)	65 (80.2%)	5 (83.3%)
NO2	47 (35.1%)	19 (38%)	27 (33.3%)	2 (33.3%)
Ozone	28 (20.9%)	6 (12%)	21 (25.9%)	2 (33.3%)
PM10	16 (11.9%)	5 (10%)	11 (13.6%)	0 (0.0%)
NOx	14 (10.4%)	2 (4%)	10 (12.3%)	2 (33.3%)
CO	9 (6.7%)	1 (2%)	8 (9.9%)	0 (0.0%)
SO2	5 (3.7%)	2 (4%)	3 (3.7%)	0 (0.0%)
PM10-2.5	2 (1.5%)	0 (0.0%)	2 (2.5%)	0 (0.0%)
PM2.5 constituents/components	8 (6%)	2 (4%)	6 (7.4%)	0 (0.0%)
Source-apportioned PM2.5	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Traffic-related PM2.5	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Non-traffic PM2.5	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Particulate matter from coal	2 (1.5%)	2 (4%)	0 (0.0%)	0 (0.0%)
Diesel PM emission	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Ultrafine Particles	5 (3.7%)	2 (4%)	3 (3.7%)	0 (0.0%)
Benzene	3 (2.2%)	0 (0.0%)	3 (3.7%)	0 (0.0%)
Wildfire	5 (3.7%)	2 (4%)	3 (3.7%)	0 (0.0%)
AQI	1 (0.7%)	1 (2%)	0 (0.0%)	1 (16.7%)
Anthropogenic NO2	1 (0.7%)	1 (2%)	0 (0.0%)	0 (0.0%)
Black Carbon	3 (2.2%)	1 (2%)	2 (2.5%)	0 (0.0%)
Elemental Carbon	2 (1.5%)	0 (0.0%)	2 (2.5%)	0 (0.0%)
CO2	1 (0.7%)	1 (2%)	0 (0.0%)	0 (0.0%)
Lead	4 (3%)	1 (2%)	3 (3.7%)	0 (0.0%)
Traffic exposure approximated by proximity to roads	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Traffic-related NOx	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Traffic-related PM	1 (0.7%)	0 (0.0%)	1 (1.2%)	0 (0.0%)
Other	2 (1.5%)	0 (0.0%)	2 (2.5%)	0 (0.0%)

[1] *Note: Percentages do not sum to 100 due to multiple selections being allowed.*

Supplementary Table 6 Consideration of additional RE variables across study types

Study Characteristics	All studies (N = 134)	Studies that explored Exposure disparity (N = 50)	Studies that assess health disparity with effect modification (N = 81)	Studies that assess health disparity with mediation (N = 6)
Used RE data in other form				
Yes	28 (20.9%)	10 (20.0%)	18 (22.2%)	0 (0.0%)
No	106 (79.1%)	40 (80.0%)	63 (77.8%)	6 (100.0%)

[1] Note: some studies are classified into multiple categories. The sum of studies across study type might not add up to the total number of studies.

Supplementary Table 7 Combinations of RE categories considered in studies

RE Categories[1,2,3]	**n (%)**
Asian, Black, Hispanic, White	27 (20.15%)
Black, White	12 (8.96%)
Black, Hispanic, White	11 (8.21%)
Asian, Black, Hispanic, Other, White	9 (6.72%)
Black, Other, White	7 (5.22%)
Asian/PI, Black, Hispanic, White	4 (2.99%)
Black, Hispanic, Other, White	4 (2.99%)
Black, non-Black	4 (2.99%)
Asian, Black, Hispanic, Native American, White	3 (2.24%)
Asian/PI, Black, Hispanic, Native American, White	3 (2.24%)
Black, Hispanic	3 (2.24%)
non-White, White	3 (2.24%)
Asian, Asian/PI, Black, Hispanic, Multiple, Native American, White	2 (1.49%)
Asian, Asian/PI, Black, Hispanic, Native American, White	2 (1.49%)
Asian, Asian/PI, Black, Hispanic, White	2 (1.49%)
Asian, Black, Hispanic, Native American, Other, White	2 (1.49%)
Asian, Black, Native American, White	2 (1.49%)
Asian/PI, Black, Hispanic, Multiple/Other, White	2 (1.49%)
Asian/PI, Black, Hispanic, Native American, Other, White	2 (1.49%)
Hispanic, White	2 (1.49%)
Hispanic, non-Hispanic	2 (1.49%)
African, Native American	1 (0.75%)
Asian, Asian, Asian/PI, Black, Hispanic, Other, White	1 (0.75%)
Asian, Asian/PI, Black, Hispanic, Multiple/Other, Native American	1 (0.75%)
Asian, Asian/PI, Black, Hispanic, Multiple/Other, Native American, Other, White	1 (0.75%)
Asian, Asian/PI, Black, Hispanic, Native American, Other, White	1 (0.75%)

Asian, Asian/PI, Black, Hispanic, non-Hispanic, Multiple, Native American, Other	1 (0.75%)
Asian, Asian/PI, Black, Native American, Other, White	1 (0.75%)
Asian, Black, Hispanic	1 (0.75%)
Asian, Black, Hispanic, POC, White	1 (0.75%)
Asian, Black, Multiple/Other, White	1 (0.75%)
Asian, Black, Other, unknown, White	1 (0.75%)
Asian/PI, Black, Hispanic, Other, White	1 (0.75%)
Black, Cuban, Dominican, Hispanic, Mexican, Puerto Rican, White-Hispanic	1 (0.75%)
Black, Hispanic, Mexican-American, Other, White	1 (0.75%)
Black, Hispanic, RE minority	1 (0.75%)
Black, Hispanic, non-White, White	1 (0.75%)
Black, Other	1 (0.75%)
High vs. low prop: Black	1 (0.75%)
High vs. low prop: RE minority	1 (0.75%)
Hispanic, POC, Other	1 (0.75%)
Other, White	1 (0.75%)
POC, White	1 (0.75%)
RE minority, White	1 (0.75%)
Social Vulnerability Index	1 (0.75%)
Three RE categorization levels: 14 Census group categories; Binary: White vs. RE minorities; Comprehensive: 6 mutually exclusive RE Groups	1 (0.75%)
non-minority, RE minority	1 (0.75%)

[1] Note 1: Black and White categories were interchangeably used with non-Hispanic white and non-Hispanic black, respectively.
[2] Note 2: Asian categories includes Asian, or specific Asian subgroups (e.g., Chinese, Japanese, etc.).
[3] Note 3: Asian/PI categories includes Asian and Pacific Islander, or specific Asian and Pacific Islander subgroups.