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Advancing Methods and Models that Promote Equity in Ambient Air Quality

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Abstract

Several groups in the United States, including communities of color and low-income communities, are frequently disproportionately exposed to ambient (i.e., outdoor) air pollution, reflecting unjust placement of emission sources, systemic bias, and historic race-based land use planning. Eliminating these inequities is critical for advancing environmental justice. This review synthesizes methodological innovations for characterizing and mitigating ambient air pollution inequities, focusing on the past 10 years, mostly in the United States. Advances in exposure assessment (e.g., empirical models, satellite remote sensing, mobile monitoring, sensor networks) provide new tools for characterizing disparities. Advances in techniques for attributing pollution to specific sources (e.g., reduced-complexity models) reveal how emission-reduction approaches may or may not eliminate disparities. Spatially targeted emission reductions are critical for eliminating relative disparities; conventional approaches (e.g., sectoral emission reductions, national concentration standards) are unlikely to eliminate those disparities. This article provides insights for effective interventions to promote equity in ambient air pollution exposure.

1. INTRODUCTION

In the past decade, a growing body of research has advanced methods to understand air pollution inequities and how to reduce or eliminate them. These advancements have uncovered new insights and opportunities for interventions that reduce pollution overall while also mitigating exposure inequity. Here, we review methodological innovations for investigating inequities in air pollution burdens, including new approaches to characterizing exposures (e.g., empirical models, mobile monitoring, sensor networks, satellite remote sensing), to attributing ambient pollution to sources [e.g., reduced-complexity models (RCMs)], and to characterizing population vulnerabilities. We review research to illustrate progress in the field and discuss areas requiring further methodological improvements. Given the scope and concentration of relevant studies, we focus predominantly on the United States, with limited reference to other contexts.

Equity assessments of air pollution burdens are not new. A small number of articles, mostly in the United States, from the 1960s (164, 165), 1970s (5, 40, 56), and 1980s (22) investigated how air pollution exposures varied by income or race. Literature reviews on environmental justice identified 17 articles as of 1992 (122), 53 articles as of 1995 (21), and, as of 2013, 307 articles specifically on air pollution (117). Here, we focus on research within the past 10 years (i.e., 2015–2025).

Environmental justice as a social movement has a long history (131). Important milestones include farmworker protests in the 1960s and 1970s to improve working conditions, including eliminating unsafe pesticide exposures; opposition in West Harlem, New York City, starting in 1968, to the siting of a sewage treatment plant and, after it opened in 1985, to its odors and emissions; protests and a lawsuit (10) in 1979 in Houston, Texas, regarding placement of a city garbage dump in an African American community; and protests in 1982 in Warren County, North Carolina, against the creation of a hazardous waste landfill.

Many of these social and political struggles have catalyzed research across diverse fields to investigate patterns and drivers of exposures to environmental hazards, including air pollution, and their disproportionate impacts on marginalized communities, including communities of color and low-income communities. More recently, air pollution research has evolved from simply documenting demographic disparities in hazard burdens to undertaking retrospective and anticipatory assessments of existing and proposed regulatory interventions; such studies evaluate the extent to which actions might simultaneously reduce exposures overall and also reduce or eliminate persistent racialized and class-based disparities.

Because of space limitations, several recent areas of environmental justice research are not covered in depth in this review. Examples include (*a*) recent advances in toxicology and epidemiology; (*b*) the social exposome, which integrates environmental, behavioral, and social determinants of health; (*c*) real-time biomonitoring, such as global positioning system (GPS)-enabled inhaler sensors used in asthma care and telemedicine-linked exposure tracking; (*d*) wearable exposure technologies such as silicone wristbands to detect time-averaged exposures to air toxics; (*e*) data integration of low-cost sensors and research-grade instruments; (*f*) double jeopardy, i.e., that groups often face both higher pollution levels and greater susceptibility to harm (86) owing to, e.g., compounding stressors such as chronic disease, limited access to health-promoting resources, occupational exposures, and cumulative environmental burdens; and (*g*) health and nonhealth outcomes research. Evidence suggests that persistent disparities in health outcomes by race and class reflect in part the disproportionate and synergistic environmental exposures (27, 69).

2. METHODOLOGICAL INNOVATIONS IN STUDYING AIR POLLUTION INEQUITY

2.1. Characterizing Exposures: Methods

Exposure disparities for ambient air pollution arise when pollution concentrations have a systematic and uneven distribution across a population. Disparities reflect (typically, spatial) correlations between pollution and specific subpopulations, i.e., reflecting the segregation of people and pollution. Relevant spatial scales vary: national or international, regional, urban/rural, within-urban, local, and hyperlocal (i.e., <100 m). The relative importance of each spatial scale can differ by pollutant and societal context (31, 110, 111). We use the term "environmental inequities" in this review to refer to unjust disparities that are due to discriminatory policies or practices, historical injustices including redlining and other racist planning, or other systemic unequal treatment or bias.

Several model- and measurement-based methods, and hybrid methods, can shed light on disparities and approaches to addressing them (60, 65, 105). The results of an analysis will depend in part on the method employed, including the spatiotemporal scales over which populations and pollutants covary (**Figure 1**).

Attributes of an ideal air pollution exposure assessment method include high precision and accuracy for a wide range of pollutants; fine spatial and temporal resolution; wide geographic domain; high validity relative to observational constraints; attribution of pollution to distinct emission sources; accessibility and resource efficiency (e.g., with respect to cost, time, expertise, computational burden); and an ability to assess not just past or present conditions, but also a wide range of hypothetical interventions (what was, what is, and what if). Actual methods will have strengths and weaknesses relative to this ideal (**Figure 1**).

Air pollution models can be broadly classified as either mechanistic or empirical. Mechanistic models represent the underlying chemistry and physics that govern the emissions, transport, transformation, and removal of air pollutants. For example, state-of-the-science chemical-transport models [CTMs; e.g., Community Multi-Scale Air Quality (CMAQ), Weather Research Forecast-Chemistry (WRF-Chem)] excel at representing physicochemical processes with high fidelity. However, CTMs are expensive: They are complex to run and have a high computational burden. They are rarely employed for large domains at spatial scales much finer than 4 km (for large domains, 12 km or 36 km is common) and are often limited to a small number of model runs. In the past decade, RCMs have emerged that emulate some of the key strengths of CTMs (e.g., source attribution) at much lower computational cost and higher spatial resolution. Examples include Intervention Model for Air Pollution (InMAP), Estimating Air pollution Social Impact Using Regression (EASIUR), Air Pollution Emission Experiments and Policy (APEEP) analysis tools (e.g., AP2, AP3; or "APX"), and the HYSPLIT average dispersion model (HyADS), all of which have found widespread application to environmental equity studies (48, 74, 79, 159). While these models differ in their underlying approach, a common strength is their ability to efficiently represent complex source-receptor relationships at spatial resolutions down to 1 km or better (130), enabling the assessment of large numbers of emissions scenarios.

Empirical models aim to predict spatial variation in observed air pollution based on statistical associations with more readily observed geographic characteristics. For example, land-use regression (LUR) models relate existing air pollution measurements (e.g., data from regulatory monitors or a targeted measurement campaign) and geographic predictor variables that describe urban form (e.g., road networks, green space) (87, 116). This approach built on research from the 1950s and later in geology and geostatistics on universal kriging and interpolation using auxiliary variables (119). LUR models for air pollution were first developed in 1997 to investigate intraurban variation (20). Later, starting in 2011, LUR was extended to national-scale modeling

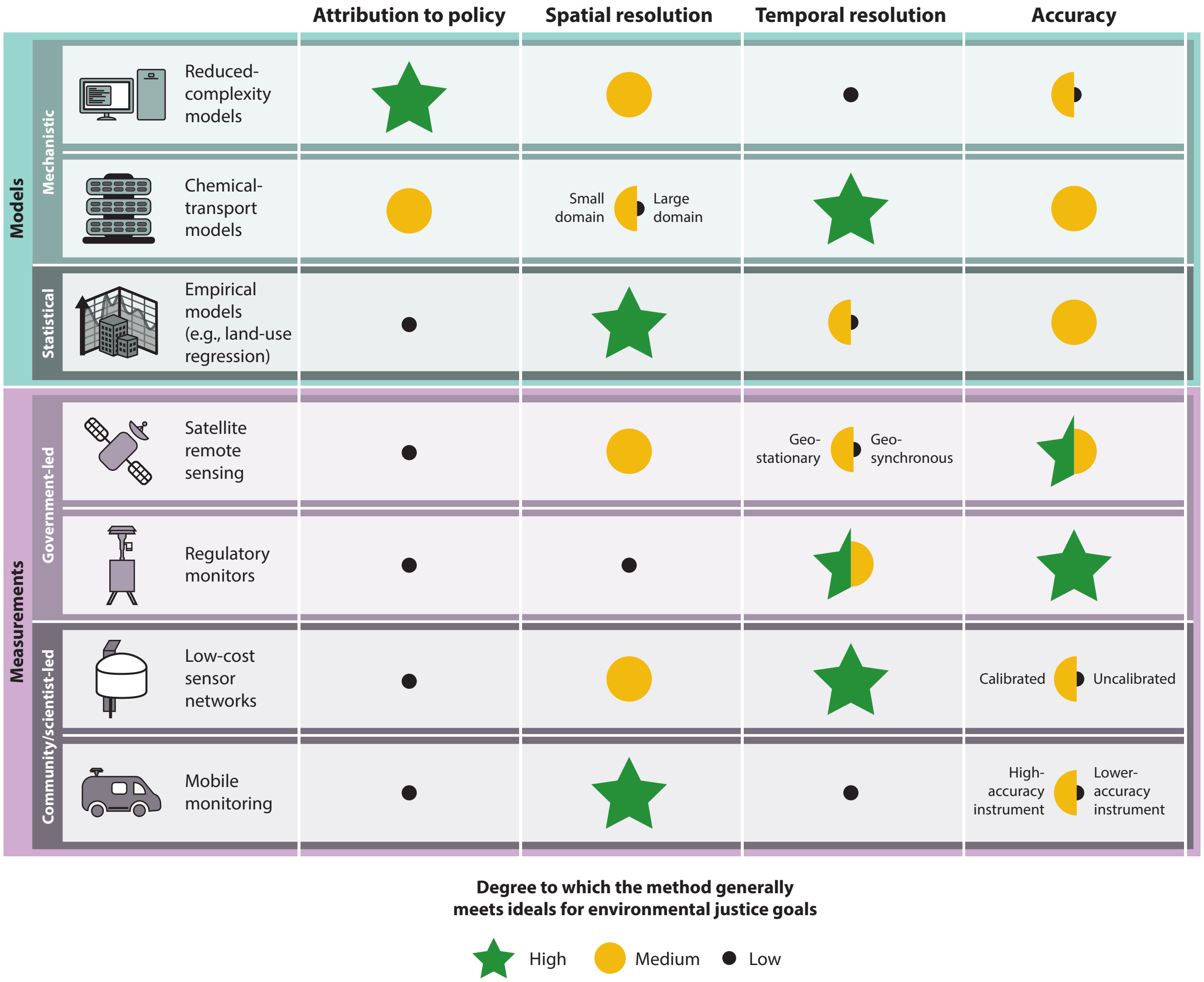

Figure 1

Methods to estimate ambient air pollution concentrations, compared to attributes for understanding disparities. Rows show seven techniques commonly used in the air pollution environmental justice literature for estimating concentrations; columns show four attributes commonly of interest for understanding disparities. For example, the first column (Attribution to Policy) refers to investigating the impacts on air pollution exposures and exposure disparities of hypothetical policies. Entries indicate typical use of each method among the environmental justice literature against ideals as follows. Attribution to a specific policy: high, the method easily facilitates policy attribution; medium, attribution is feasible but laborious; low, impossible, impractical, or uncommon. Spatial resolution: High, sub-kilometer; medium, 1–5 km; low, >5 km. Temporal resolution (i.e., time step of the estimate): high, hourly or higher frequency; medium, daily; low, less resolved than daily (e.g., monthly/annual). Accuracy: high, considered the most accurate method; low, individual point estimates may be wholly unreliable, but insights aggregated across the full modeling domain are robust; medium, between those two extremes. In some entries, two icons (e.g., medium/low) are given for reasons mentioned in the figure (e.g., accuracy of low-cost sensors depends on calibration) or because typical use cases vary (e.g., accuracy for reduced-complexity models depends on the model and the emissions inventory employed).

(129). A recent intercomparison of six national-scale models for the United States reported relatively good levels of agreement in annual-average predictions (11). Global-scale LURs also exist (107), and there are LURs for multiple countries. For additional details about LUR, a recent article by Ma et al. (113) reviews LUR research from 2011 to 2023.

LUR models excel at representing fine-scale spatial variation in air pollution, often at better than 100 m resolution. LUR is generally unable to provide causal/mechanistic attribution of the emission sources that drive air pollution patterns. As such, empirical models such as LUR can characterize disparities (37, 38, 110, 143, 144, 176) but generally not the impact of mitigating specific emissions sources. By definition, LURs will perform poorly when concentrations are not well correlated with land-use characteristics (i.e., if the independent variables are poorly correlated with the dependent variable); for example, LUR will generally perform better for primary pollutants emitted on-roadway than for secondary pollutants with spatial patterns uncorrelated with land use. Land-use predictors (e.g., population density, road proximity) may be correlated with both air pollution and socioeconomic characteristics; those correlations may reflect real spatial conditions, but they can complicate the interpretation of model-estimated disparities.

Direct measurement of air pollution provides an observational basis for understanding air pollution disparities. Measurements from regulatory monitors play an important role in assessing long-term trends and compliance with air quality standards. However, taken alone, these networks almost uniformly lack the spatial resolution to properly assess intraurban pollutant disparities, unless coupled with other statistical techniques such as LUR (36, 172). In addition, the placement of monitors may be biased with respect to specific demographic groups, such that disparities estimated using those data may also be biased (172).

Two emerging technologies—mobile monitoring and dense sensor networks—offer complementary strengths for assessing patterns of air pollution at intraurban spatial scales (7, 32). Mobile monitoring can provide hyperlocal (30–100 m) estimates of time-averaged spatial patterns for many pollutants using robust, high-quality monitoring devices (8), providing valuable information about how fine-scale patterns drive disparities (32, 35, 152). In contrast, crowdsourced sensor networks excel at representing the temporal patterns of pollution within and between communities for a smaller number of pollutants and can better capture the influence of episodic or cyclical pollutant dynamics on exposure disparities (112, 123). Increasing efforts are underway to integrate the relative strengths of these two observational paradigms into hybrid models (71, 109, 115). While these in-situ methods can provide unusually rich information at fine scales within individual neighborhoods, the high cost of running such dense networks limits their spatial extent, which limits the ability to understand disparities over broader length scales.

Satellite remote sensing can provide comprehensive spatial coverage across large geographic domains. Multiple pollutants—notably fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2)—have satellite data products with fine-scale (1–10 km) estimation of pollutant levels; new instruments and data processing techniques increasingly provide broad, rich information on multiscale disparities (46, 51, 86, 98). Satellite data are commonly included in large-scale LUR models.

2.2. Characterizing Exposure and Exposure Inequities: Findings

Research from the past 10 years on air pollution in the United States consistently shows that people of color and low-income groups experience higher exposures to $PM_{2.5}$, NO_2, and other pollutants (12, 19, 26, 36, 39, 41, 64, 83, 103, 111, 133, 135, 138, 140, 150, 155, 158, 161, 171). Although income is a relevant determinant, race often emerges as a stronger predictor of pollution disparities (12, 36, 39, 55, 64, 91, 111, 120, 158, 160, 171). That conclusion—that race is more important than income as a statistical predictor of exposures—is consistent with findings from the likely first investigation on this topic, published in 1972 (56).

Mechanisms and events leading to this outcome include historical segregation and discriminatory land-use policies that cause the siting of highways, industrial zones, power plants, and other sources of pollution disproportionately in vulnerable areas (19, 39, 41, 83, 100, 103, 135, 150, 161, 178). Over time, overall pollution levels have generally declined in most parts of the United States [although forest fire smoke and other recent changes have reversed that trend in some regions (24)]; as described next, disparities have sometimes improved and sometimes not (see below).

Differentiation between absolute disparities and relative disparities is relevant here and, as discussed below, when considering reducing or eliminating disparities. Absolute disparity refers to differences, in units of concentration or dilution volume [e.g., $\mu g/m^3$ or parts per billion (ppb)]. Relative disparity [i.e., the difference normalized to (i.e., divided by) a reference concentration, such as the population average concentration] typically has units of percent difference or is reported unitless (e.g., 15% or 0.15). The distinction between absolute and relative disparities can be relevant when comparing contexts where average exposures vary.

For example, consider a hypothetical comparison between subpopulation A and the population average for two locations, X and Y. In location X, the average exposure is 1 ppb for the overall population and 1.5 ppb (i.e., 50% higher than the overall population) for subpopulation A. In location Y, the average exposures are 0.1 ppb (overall population) and 0.2 ppb (subpopulation A; i.e., a 100% increase above the population average). The location with the greater disparity is X if considering absolute disparity [0.5 ppb (X), 0.1 ppb (Y)] but is Y for relative disparity [50% (X), 100% (Y)].

The recent literature on disparities and their changes over time highlights the importance of the relative versus absolute difference. For example, Liu et al. (110) showed that for many cases in the United States, absolute disparities have decreased over time yet relative disparities have not. This result underscores the critical importance—when quantifying or communicating disparities or seeing how they differ over time or space—of distinguishing absolute versus relative.

Air pollution exposure disparities observed in the United States have, to some extent, also been observed internationally. For example, in Mexico, satellite data indicate that poorer localities face higher $PM_{2.5}$ levels (29). Sub-Saharan Africa shows extreme pollution burdens, affecting largely low-income groups in fast-growing cities with limited environmental oversight (96). In India, caste, religion, education, and income interact to create disproportionate impacts on, for example, Scheduled Caste, Other Backward Class, low income, and Muslim communities (15, 30, 49). Across Europe, immigrant and lower-income populations frequently experience higher pollution exposures (54, 55). In London and Jakarta, commuting patterns further exacerbate exposure disparities, as lower-income commuters who predominantly rely on buses experience higher pollutant concentrations than do wealthier individuals who travel by private cars (16, 138).

In contrast, for China, the patterns reported are the opposite: Higher socioeconomic status correlates with greater exposure (173). The potential causes for these patterns are many, including the level of economic development and the role of economic development in shaping pollution.

Satellite-based remote sensing can shed light on environmental disparities in air pollution, in part by providing high-resolution data on pollutants such as NO_2 and $PM_{2.5}$ (26, 28, 46, 47, 51, 52, 57, 65, 67, 76, 84, 98, 99, 100, 102, 145, 166). Multiple studies using satellite-derived estimates of air quality reveal that marginalized communities, including low-income and racial minority populations, face disproportionately high exposures to air pollutants (26, 28, 33, 45, 47, 51, 52, 97, 98, 100, 102, 145). For example, TROPOMI-derived NO_2 measurements reveal inequities in urban and rural settings, with Black, Hispanic, and Asian populations consistently reporting higher average exposure levels relative to White communities (46, 47, 51, 52, 98, 99). Satellite-based $PM_{2.5}$ estimates have also linked heightened pollution burdens to increased mortality and morbidity, particularly in economically disadvantaged neighborhoods (26, 28, 76, 84, 100). Satellite-based estimates have documented inequalities in pollution levels at schools (12, 33).

Satellite-based research also reveals uneven distribution of factors somewhat related to air pollution, such as disparities by socioeconomic status in access to urban nature (166). Satellite data can offer historical perspectives, enabling the detection of persistent pollution disparities despite overall improvements in ambient air quality (76, 99, 100).

Additional examples of recent findings regarding disparities and emission-reduction approaches to reduce disparities in the United States include the following. Yoo et al. (177) found that non-White groups consistently face disproportionate exposure to air pollution. They reported that, on average, Hispanic people encounter workplace $PM_{2.5}$ levels of 8.50 $\mu g/m^3$ (compared to 8.05 $\mu g/m^3$ for White people), and Black people experience residential NO_2 levels of 23.34 ppb (compared to 21.70 ppb for White people) (177). Mikati et al. (121) found that Black populations nationally had 1.54 times greater $PM_{2.5}$ exposure from nearby facilities than did the overall population, surpassing socioeconomic-based disparities.

In understanding exposure disparities, there are important interrelationships between race/ethnicity, income, urbanicity, and pollution levels. On average, wealthier households tend to concentrate in larger cities (versus in smaller cities or in rural areas). Pollution levels tend to be higher, on average, in larger cities. Investigating this interrelationship, Clark et al. (36) examine how geography, race/ethnicity, and income intersect for NO_2 exposure patterns: After subdividing urban areas by size (small, medium, large), the pattern observed is, for each urban area size, (modestly) higher exposures for lower-income households and, to a greater extent, for racial/ethnic minorities. If they instead had considered all urban areas in one analysis, instead of subdividing by urban area size, those trends would appear differently or would disappear.

Exposure patterns may vary across national, state, and local scales. At the same time, however, some patterns are common and are repeated across many geographies. Liu & Marshall (111) demonstrated how different geographic scales of variability in NO_2 and $PM_{2.5}$ pollution levels contribute differently to pollution exposure inequities as well how those patterns can shed light on the underlying causes for disparities. Dressel et al. (51) report that for satellite-based NO_2 disparity analysis, the optimal spatial scales for measuring inequalities are larger than atmospheric dispersion gradients, suggesting that suburban scale observations may not always be necessary for understanding citywide pollution disparities. That finding is consistent with results from Chambliss et al. (31), who used extensive mobile monitoring across the San Francisco Bay Area to map hyperlocal air pollution patterns (pollutants mapped included NO, NO_2, black carbon, ultrafine particles); they found that while significant pollution hotspots exist at the block level, racial and ethnic disparities were driven primarily by regional-scale concentration differences rather than local gradients. This finding reinforces that addressing environmental inequity requires interventions at multiple spatial scales. Regional approaches are particularly important for reducing systematic exposure disparities.

2.3. New Approaches for Characterizing Marginalization and Other Vulnerable Populations: New Metrics, Methods, and Findings

New methods are also integrating exposure science and social epidemiology approaches to characterize disparities in air pollution exposures and their health effects among marginalized groups based on demographic characteristics that transcend traditional demographic measures such as race/ethnicity, poverty, and income. Alternative demographic characteristics include indicators of historical racism, voter disenfranchisement, linguistic isolation, tenancy, and housing quality.

For example, there has been a surge of studies examining the association between historical redlining and current exposures to air pollutants and proximity to air pollution sources. Many environmental problems disproportionately faced by communities of color and the poor in the

United States are rooted in discriminatory policies and actions implemented generations ago by local, state, and federal governments. In one such policy, known as redlining, the federal Home Owners' Loan Corporation (HOLC), in trying to revive the housing market in the 1930s in the wake of the Great Depression, graded and mapped how risky neighborhoods were for real estate investment (141). Neighborhoods composed of largely low-income, immigrant, or Black residents were deemed "hazardous" or "definitely declining" and mapped in red (i.e., redlined), while Whiter and wealthier communities were considered "best" or "still desirable." These legacies remain imprinted on the environments of neighborhoods today. In 2022, Lane et al. (106) examined the association between historical redlining and 2010 estimates of $PM_{2.5}$ and NO_2 and found a consistent and nearly monotonic association between HOLC grade and pollution levels, with especially pronounced (>50%) increments in NO_2 levels between the highest (grade A) and lowest (grade D) graded neighborhoods. Intraurban disparities for NO_2 and $PM_{2.5}$ were substantially larger by historical HOLC grade than they are by race/ethnicity, although within each HOLC grade, disparities in air pollution exposure by race/ethnicity persisted, indicating that redlining was only one of the many racially discriminatory policies that impacted communities.

Gonzalez et al. (2023) investigated disparities in exposure to urban oil and gas wells among HOLC-graded neighborhoods in 33 cities from 13 states (69). For the 17 cities with 1940 census data, the authors used propensity score restriction and matching to compare exposures in neighborhoods with similar 1940 sociodemographic characteristics but differing HOLC grades (69). Their results demonstrated a strong association, with redlined neighborhoods having nearly twice the density of oil and gas wells than otherwise comparable, nonredlined, neighborhoods.

Similar findings for redlining and air pollution nationwide (94, 106) have also been reported for Pittsburgh, Pennsylvania (148), Seattle, Washington (18), and Denver, Colorado (17); for schools in New York City (95); for multiple air pollution–related health outcomes such as asthma and adverse birth outcomes (14, 82, 93, 126, 127); for siting of power plants (43); and for many other environmental factors (53). Analysis of the history of specific infrastructure associated with emitting sources (e.g., highways, rail lines) in Denver and nationally reveals the impact of redlining, yet it also reveals that disparities in locations for that infrastructure happened before, during, and after redlining (17, 18). Redlining is an important example of racist urban planning, but it is not the only one; it is a focus of study in part because redlining maps have survived to the present day and have been digitized.

Other studies have analyzed exposure equity related to large greenhouse gas sources, including methane superemitters. These point sources release large amounts of methane across many industries and also emit harmful co-pollutants, including air toxics and criteria air pollutants. For example, oil and natural gas production and distribution emit hazardous air pollutants in addition to methane, including PM and nonmethane volatile organic compounds, which are ozone precursors (2, 59, 142) and several of which are associated with negative health impacts, including neurological damage, adverse perinatal outcomes, birth defects, and cancer (90, 163). Air quality sampling during the largest point-source methane release ever recorded in the United States—the Aliso Canyon Natural Gas Storage Field active blowout in 2015—revealed elevated levels of several hazardous air pollutants, including benzene, a carcinogen and reproductive toxicant (58). An exposure study used the location (census block groups), category (e.g., landfill, refinery), and emission rate of California methane superemitters from Next Generation Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-NG) flights conducted between 2016 and 2018 to undertake an equity analysis of more than 430 methane superemitters in California (27). Results from fully adjusted logistic mixed models showed environmental inequity in methane superemitter locations. For example, for every 10% increase in non-Hispanic Black residents, the odds of exposure increased by 10% [95% confidence interval (CI): 1.04, 1.17]. Similar disparities for Hispanic and

Native American populations were observed, but not with area-level measures of socioeconomic status. Increasing proportions of non-White populations and lower voter turnout were also associated with higher superemitter emission intensity. At present, research is mixed regarding whether carbon markets worsen environmental inequity aspects of air pollution exposure (3, 42, 81, 108, 153).

Finally, wildfires are increasing in their frequency, intensity, and duration, resulting in more ubiquitous exposures to wildfire smoke; these rising exposures are reversing the progress made over the past decades in air pollution reduction (23). Several health endpoints are associated with wildfire smoke exposures, including asthma exacerbations, chronic obstructive pulmonary disease, and elevated risk of preterm birth (34, 73, 125, 134, 137, 139). Compared to nonwildfire $PM_{2.5}$, wildfire-related $PM_{2.5}$ may be more toxic (1) and may contain higher concentrations of oxidative and proinflammatory compounds and of ultrafine particles (114, 118, 167, 174). Evidence suggests that more-vulnerable communities—including native populations, low-socioeconomic-status populations, and outdoor agricultural workers—may have higher-than-average exposure to wildfire smoke (92, 146, 147). A recent study examined the extent to which housing characteristics, including home size, year of construction, cooling type, and renovation status, influenced the association between wildfire smoke exposure and risk of preterm birth in California (154). Results showed elevated effects for people living in unrenovated homes, those using evaporative cooling systems, and those using central air conditioning units (149), suggesting the importance of housing quality as a measure of social vulnerability to the adverse effects of wildfire smoke.

Another aspect of defining vulnerable communities involves recognizing that populations can change and that environmental improvements can, at times, catalyze demographic changes. The term "pollution gentrification" refers to cases where environmental improvements in low-income or overburdened communities end up attracting wealthier populations, thereby displacing original residents (39, 41, 54, 77, 103, 120, 133, 140, 158, 171).

2.4. From Documenting Disparities to Understanding Approaches to Reduce/Eliminate Them

Environmental justice scholarship can and must move beyond documenting problems to propose and assess potential solutions. Here, we discuss methodological innovations for satellite-based data and RCMs, which have been used to shed light on reducing/eliminating disparities in exposure to ambient air pollution.

2.4.1. Satellite-based methods. Refinements in satellite data integration and in LUR and fused modeling have enhanced exposure assessments to illuminate localized disparities that may be overlooked by ground-based monitoring (57, 65, 67, 88, 97, 102). As a result of these innovations, satellite observations can also guide policy interventions by identifying emission hotspots linked to industrial activities or heavy traffic, thereby helping to prioritize environmental inequity measures (52, 88, 97, 145). Satellite observations reveal weekday/weekend variations in urban NO_x emissions (e.g., because of temporal patterns in diesel commercial vehicle traffic); this attribute can be used to enhance our understanding of emission dynamics and exposure patterns (66, 156, 157, 169, 171). Demetillo et al. used weekend/weekday differences in satellite-derived pollution levels to estimate contributions from diesel truck traffic for Houston, Texas (47), and for 52 US cities (46). For the 52 US cities, these analyses indicate that "a 62% reduction in diesel emissions would decrease race-ethnicity and income inequalities by 37%" (46, p. 1). Emerging evidence suggests that integrating satellite observations with community-level data can inform adaptive strategies and promote equitable policy outcomes (145).

2.4.2. Reduced-complexity models. Modeling can link equity outcomes, and changes in those outcomes, to specific emission reductions. Comprehensive CTMs have been used to estimate disparity associated with limited emissions scenarios over a small geographic domain (26, 117, 128, 168). Adjoint and direct decoupled methods could be developed for equity-oriented applications, but examples are limited (136). As described above, CTMs and related methods (e.g., adjoint modeling) are computationally expensive, especially if the modeler wishes to have small grid cells. The high computational cost hinders their widespread use for characterizing disparities, making CTMs prohibitively expensive for many environmental inequity applications.

RCMs aim to overcome these limitations by sacrificing some degree of fidelity in order to dramatically reduce computational cost and, often, to increase spatial precision. As mentioned above, four examples of RCMs commonly used for equity-oriented studies are InMAP, EASIUR, APX, and HyADS (48, 74, 79, 159). Each approach is briefly discussed here; detailed intercomparisons exist (9, 25, 62, 85, 150).

InMAP is an Eulerian grid model that estimates $PM_{2.5}$ concentrations by parameterizing a steady-state solution to the advection-diffusion reaction (159). InMAP and the InMAP source-receptor matrix (ISRM; a library of InMAP runs) have been used in several analyses (6, 50, 64, 70, 72, 77, 103, 120, 130, 132, 133, 135, 151, 158, 160, 161). EASIUR uses linear regression to estimate social cost per-unit emission from population and atmospheric variables (61, 78, 79). EASIUR and its source-receptor matrix (80) have been used in several studies on air pollution and environmental equity (4, 63, 178). APX and HyADS estimate marginal changes in $PM_{2.5}$ concentration using dispersion modeling–derived source-receptor frameworks (48, 74, 124). APX, which employs Gaussian plume modeling, has been used in several equity-oriented analyses (83, 91, 150, 155). HyADS uses an air parcel trajectory model to estimate concentrations from point sources. HyADS has been used mainly to study, for example, exposure to coal plant emissions (44, 75).

These models have several important limitations. RCMs often rely on training data from higher-fidelity models, which may limit applicability for far-future or far-past analysis. In addition, all four RCMs typically estimate annual average $PM_{2.5}$ concentrations; with only a few exceptions, they are generally not used for other pollutants or timescales.

3. APPROACHES TO REDUCE AND ELIMINATE DISPARITIES

As scientific consensus converged around the nature of exposure disparities, the next step is to identify strategies to eliminate them. To identify and discuss disparities, population exposures are often summarized using a population-weighted mean concentration, from which disparity can be calculated, as mentioned above, in absolute (concentration units) or relative (percent difference) terms (102, 133, 135, 171). While absolute disparity is important for estimating disparity in health outcomes, the relative disparity is also important because it quantifies the systemic inequality between two groups (104).

Sector-specific research highlights trucking corridors, heavy industry, and power generation as examples of contributors to localized hotspots, including in overburdened communities (26, 31, 55, 64, 72, 77, 91, 103, 120, 151, 161, 162, 178). Policies aimed at aggregate emission reductions, including aggregate emissions from specific economic sectors, might leave inequities unchanged and in some cases might exacerbate inequities, unless they explicitly spatially target emissions impacting historically overburdened communities (64, 91, 133, 135, 150, 171). Overall, these findings underscore that social and demographic factors, including race and class, shape who benefits from air quality improvements and who remains exposed. They point to the need for spatially targeted equity-focused interventions in environmental regulation.

Polonik et al. (135) indicated that certain climate policies, despite reducing absolute $PM_{2.5}$ exposures, might worsen relative disparities among communities of color by up to 12%. Jordan et al. (92) showed that while racial disparities in $PM_{2.5}$ from transportation and power generation will likely persist through at least 2040, aggressive interventions could eliminate these differences by 2050. McNeil et al. (120) found that electrifying heavy-duty trucks combined with grid decarbonization could reduce absolute air pollution–related premature mortality by up to 84% in disadvantaged communities by 2050, but relative disparities persisted or even increased, from 0.7% currently to 6.9% by 2050, indicating disproportionate benefits for nondisadvantaged communities.

As the above examples illustrate, there are two common approaches for identifying the features of a given policy that lead to changes in disparities. One approach is retrospective: evaluating the effects of historical policies. For example, observationally constrained $PM_{2.5}$ surfaces have shown that aggregate air pollution benefits from the Clean Air Act have maintained relative inequality across decades (39, 87). Evaluations of source-specific policies (e.g., mobile source strategies, cap-and-trade, and shifts from coal electricity) have suggested that substantial emissions reductions do not necessarily yield reductions in relative disparity in exposure or health outcomes (3, 42, 44, 75, 103).

A second common approach is prospective: estimating how exposure disparities could change in the future. For example, because many climate change mitigation policies have air pollution cobenefits, many analyses have aimed to identify climate change mitigation pathways that also benefit equity (64, 77, 91, 133, 135). Across these analyses, the climate change mitigation pathways that tend to reduce the absolute air pollution exposure disparity the most are those that have a dedicated focus on reducing sources that disproportionately impact the overburdened population of interest. For example, future vehicle electrification policies have been extensively modeled to demonstrate that vehicle electrification efforts in overburdened communities need to substantially outpace domain-wide adoption in order to achieve equity benefits (26, 83, 89, 120, 132, 168, 175). Identifying emission-reduction approaches that achieve a triple win (i.e., climate change mitigation, overall air quality, and equity aspects of air quality) is an important topic on which to expand in future research.

In addition to modeling individual policies, recent publications have made efforts to establish and quantify paradigms for equity-oriented environmental policymaking. One approach—which in part builds on, and aims to add an equity focus into, the intake fraction literature (13)—proposes that policymakers target the emission source categories that most disproportionately affect overburdened people (160). A second approach is location-specific policy, which emphasizes the importance of where an intervention occurs. Location-specific policy reduces disparities substantially more efficiently than do sector-wide controls, so long as the locations are chosen appropriately (170, 171).

Building on these paradigms, investigators introduced a framework for screening whether a policy will reduce disparities. Here, the absolute disparity in exposure to a source of air pollution for a specific group is decomposed into three components: total emissions; an average exposure factor linking emissions to population-wide exposure; and relative inequality, reflecting spatial proximity and levels of segregation of people and pollution (104). Unless the lattermost term (relative inequality) is reduced, a policy cannot eliminate inequality in exposure without fully mitigating emissions.

Future work that aims to identify equity-oriented pathways for emissions controls or sustainable infrastructure development should begin by acknowledging that exposure inequality reflects the unequal distribution of emission sources relative to populations. Without attention to where and next to whom sources are located, today and in the future, environmental policies are likely to fail to achieve reductions in disparity. This insight has been a central tenet of the environmental justice movement since its inception and is consistent with many of the demands of advocates.

4. CONCLUSIONS AND GOING FORWARD

This review highlights the considerable progress over the past 10 years in scientific and engineering methods for understanding inequities in exposure to ambient air pollution and potential steps to reduce or eliminate those inequities. New techniques in exposure assessment (e.g., using satellite remote sensing, mobile monitoring, empirical models, sensor networks) have provided new quantification of disparities, including enhancing our ability to characterize exposure disparities with greater precision and spatial resolution. The evidence consistently demonstrates that marginalized communities, particularly those of color and low-income groups, bear disproportionate air pollution burdens, a pattern that reflects present-day and historical discriminatory practices. New techniques in attribution of pollution (mainly, RCMs; also, use of CTMs and satellite remote sensing) have provided new insights into approaches to air quality management that may or may not reduce or eliminate disparities, especially relative disparities. Based on evidence from retrospective evaluations and future scenario modeling, reducing or eliminating unjust disparities will require prioritizing the location and distribution of emission sources that are near vulnerable and structurally marginalized communities. Notably, conventional approaches (e.g., sectoral emission reduction; National Ambient Air Quality Standards) are ineffective at eliminating relative disparities. Finally, research has advanced methods for defining overburdened communities.

Several aspects and topics described above would benefit from further methodological improvements. For example, open questions remain about how best to characterize disparities, including the interconnections between demographic attributes (e.g., race/ethnicity, income), geography (e.g., urban versus rural; small versus large cities), pollutants, and changes over time. Methodological weaknesses always exist; examples here include the computational cost limitations of high-fidelity models for broad applications and the limited applicability of some RCMs to pollutants other than $PM_{2.5}$ or to nonannual timescales.

We assert that these research questions should not be held as an excuse for inaction or delay of action in policy contexts. As mentioned above, observed health disparities reflect exposure disparities (27, 69). Enough is known to continue and expand policy efforts to reduce or eliminate already-documented unjust disparities in exposure and risk.

Another area for improvement reflects the methods available to investigate policy-oriented questions (e.g., what would be the environmental equity impacts of a potential future policy; how can future policy efficiently reduce or eliminate unjust disparities; what are the environmental equity impacts of historical policies or actions): This work should become more embedded and routine in policy analysis. More work is also needed to integrate air quality equity concerns with concerns about other intersectional exposures, such as access to greenspace, urban heat islands, climate change adaptation and mitigation, and cumulative impacts across pollutants (and across nonpollutant exposures).

Evidence identifies ways in which uncertainties in measurements and models may mean that disparities are underestimated. For example, satellite data indicate that emission inventories may be overestimated in wealthy areas and underestimated near warehouses (68). The nonrandom placement of regulatory monitors may mean that disparities estimated directly via monitoring data (rather than via empirical models) are underestimated (172). Clean Air Act violations preferentially happen in communities of color (101); this record suggests that emission inventories may be underestimated for those communities. Additional research could usefully understand how uncertainties in current methods lead to disparity estimates being under-/overestimates.

Important insights and findings that we anticipate researchers tackling in the next 10 years include the following: cumulative and intersectional impacts; long-term efficacy of policy interventions, including those that embed equity goals in their design; and other environmental stressors (e.g., climate stressors). RCMs aim to emulate results from higher-fidelity models; with the current revolution happening in artificial intelligence and machine learning, we anticipate that new approaches to RCMs and empirical models will open new doors to equity-related questions in air pollution. Similarly, a small number of publications have demonstrated using satellite data for estimating emissions and emissions attribution (46, 47, 100), and the recently launched geostationary satellite TEMPO provides a new category of spatiotemporal concentration data; future developments should extend research capabilities in methods to promote equity in air quality. Last, and perhaps most important since this topic cuts to the center of why environmental equity policy and action are needed, continued and additional effort is critical for including community voices in decision-making. Future insights will move well beyond documenting the problem by embedding data- and community-driven tools into regulatory decision-making (e.g., siting, permitting, and land-use decision-making).

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