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Critical Review

Selecting Data Analytic and Modeling Methods to Support Air Pollution and Environmental Justice Investigations: A Critical Review and Guidance Framework

Rivkah Gardner-Frolick, David Boyd, and Amanda Giang*

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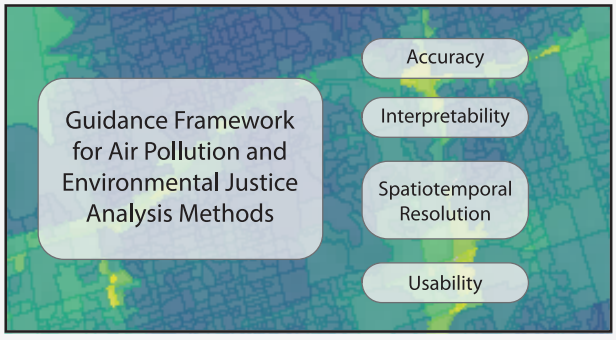
ABSTRACT: Given the serious adverse health effects associated with many pollutants, and the inequitable distribution of these effects between socioeconomic groups, air pollution is often a focus of environmental justice (EJ) research. However, EJ analyses that aim to illuminate whether and how air pollution hazards are inequitably distributed may present a unique set of requirements for estimating pollutant concentrations compared to other air quality applications. Here, we perform a scoping review of the range of data analytic and modeling methods applied in past studies of air pollution and environmental injustice and develop a guidance framework for selecting between them given the purpose of analysis, users, and resources available. We include proxy, monitor-based, statistical, and process-based methods. Upon critically synthesizing the literature, we identify four main dimensions to inform method selection: accuracy, interpretability, spatiotemporal features of the method, and usability of the method. We illustrate the guidance framework with case studies from the literature. Future research in this area includes an exploration of increasing data availability, advanced statistical methods, and the importance of science-based policy.



KEYWORDS: *Environmental Justice, Air Pollution, Methods, Personal Exposure, Kriging Interpolation, Land Use Regression, Machine Learning, Chemical Transport Modeling*

■ INTRODUCTION

Decades of research have shown that air pollution has detrimental effects on human health[1−8] and that these health risks are disproportionately borne by vulnerable communities that have experienced historical and ongoing marginalization.[9−18] Air pollution is a large contributor to global mortality. Ambient $PM_{2.5}$ (particulate matter with a diameter under 2.5 μm) was the fifth-highest global mortality risk factor in 2015, causing 4.2 million premature deaths.[8] $PM_{2.5}$ and other air pollutants contribute to the global burden of disease through cardiopulmonary disease, cerebrovascular disease, respiratory illnesses, and cancer.[8] Given the serious adverse health effects associated with many pollutants, air pollution is often a focus of environmental justice (EJ) research.[1−18] EJ concerns the equitable "distribution of environmental benefits and burdens among populations, as well as the fairness of relevant decision-making processes."[19] The COVID-19 pandemic has underscored the stark health inequities that still exist in the 21st century[20−23] and the ways in which environmental determinants of health can contribute to these inequities.[24−26] Global movements for racial and other dimensions of social justice are bringing renewed attention to the synergistic effect of environmental hazards and social determinants of health.

This critical review focuses on methods for evaluating the linkages between air pollution and environmental injustice. Communities, activists, researchers, and decision makers can benefit from knowing to what extent different populations are exposed to air pollution in order to understand current patterns of exposure inequities, identify their drivers, prevent disproportionate burdens from worsening, and take corrective action through policy or consistently enforcing existing standards. There are a range of methods used to estimate ambient pollution concentrations and human exposure at the individual and community levels. These methods typically grapple with the reality that although air quality can vary at fine spatial and temporal scales,[27−30] in situ measurement at all locations and times of interest is seldom feasible. To improve upon sometimes sparse monitoring data and enable the connection between pollution concentration and sociodemo-

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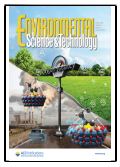

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graphic variables, many studies use modeled or derived concentration estimates to cover the complete spatial and temporal domains of interest. Methods to generate these estimates range from spatial coincidence methods to chemical transport models, each with strengths and limitations. However, when concentration estimates (or their proxies) are used to examine issues of environmental injustice, there may be additional, unique requirements that inform method selection, beyond those employed in other contexts. This critical review aims to address the range of methods used in EJ analyses through a review of how methods have been applied in past EJ studies, development of a guidance framework to inform method selection, illustration of the framework using case studies from the literature, and exploration of future research directions.

AIR POLLUTION AND ENVIRONMENTAL INJUSTICE

Air pollution is a complex mixture of compounds with a wide range of adverse human health effects. Gases ranging from criteria pollutants, which are regulated by health-based standards in the US (NO_2, SO_2, and CO), to air toxics can occur due to industrial activity, agriculture, or combustion processes.[31,32] These gases contribute to health effects such as cancer and respiratory problems.[5,7] Much of the research on health effects has focused on particulate matter (PM), especially fine particulate matter ($PM_{2.5}$). PM has been shown to contribute to cardiopulmonary and respiratory illness, cancer, and mortality.[1−5,33] Toxic components within PM such as heavy metals can additionally cause neurological effects, increased blood pressure, anemia, and kidney damage.[5,6] As such, air pollution is a large contributor to global mortality and morbidity, responsible for an estimated seven million premature deaths annually.[8] The health effects of air pollution are not restricted to highly polluted locations. Many areas around the world thought to have relatively "clean" air still experience the detrimental effects of air pollution, as even low or moderate levels can impact human health.[7,8,34−37] Studies on concentration−response curves between PM concentrations and a range of human health effects indicate that the curves are generally supralinear, with a steeper slope for low-moderate levels of PM, although this can differ between health effects.[35,36,38,39] There may be no safe concentration for many air pollutants, and exposure to mixtures of pollutants can exacerbate adverse health effects.

Air pollution affects populations unequally. The concept of distributive environmental injustice describes how unequal environmental burdens can fall on different populations due to sociodemographic characteristics. Robert Bullard provides a concise definition of EJ: "Environmental justice embraces the principle that all people and communities are entitled to equal protection of environmental and public health laws and regulations."[40] A longer statement on the tenets of EJ is found in the document created by the First National People of Color Environmental Leadership Summit held in 1991.[41] Broadly, EJ falls into three categories—distributive justice, procedural justice, and recognitional justice. Distributive justice includes the fair distribution of environmental harms (i.e., exposure to air or water pollution) as well as benefits (i.e., access to greenspaces).[42] Procedural justice refers to equitable weight given to different voices in processes that affect a group's environment. For example, during the siting process for a facility or the implementation of an environmental policy. Finally, according to Whyte, "recognition justice requires that policies and programs must meet the standard of fairly considering and representing the cultures, values, and situations of all affected parties."[43] All three categories are relevant to air pollution. Although air pollution studies typically focus on distributive injustice, procedural and recognitional injustice are also highly relevant to exposure inequities.[16,19] Procedural and recognitional justices are necessary to empower communities and can facilitate distributive justice. Better concentration estimates can strengthen evidence for the existence of all forms of EJ and can motivate corrective action.

Even countries with good air quality overall, such as Canada or the US, can exhibit hotspots or areas with elevated concentrations of air pollutants.[27,44,45] Hotspots can affect sociodemographically vulnerable communities unequally due to both disproportionate exposure to elevated concentrations of pollutants and other factors that compound the effects of air pollution.[9−18] Some populations have an increased risk of adverse health effects from air pollution, including children, older adults, and low-socioeconomic status individuals.[1,46,47] Increased risk can be due to a number of factors related to structural inequities, including stress, diet, exercise, access to healthcare, and access to jobs.[1,5,48,49] These social determinants of health create a "double jeopardy" for historically marginalized populations living in an EJ community where air pollution can have a larger effect on health.

Linking environmental risks and benefits to human well-being has long been central to the activism and advocacy of many communities, including Indigenous, Black, and other communities of color.[50,51] For example, one of the first major actions taken against environmental injustice occurred in 1968 when Black Memphis Sanitation workers led a strike for better working conditions and equal pay.[52] These communities began to coalesce under the common banner of "environmental justice" in the US. Although EJ research is perhaps historically the most prolific in the US, it is expanding in many other areas of the world, with national level studies conducted in Italy,[53] New Zealand,[54] Australia,[42] India,[55] England,[56] and Canada,[57] among other recent work. Broadly, these studies have found evidence for the wide utility of an EJ framework to examine differences in pollution exposure across vulnerable populations, including dimensions such as racialization, socioeconomic status, immigration status, Indigenous identity, linguistic isolation, rural−urban residence, and intersections of the aforementioned. EJ has also expanded conceptually and has come to include water justice and climate justice, among other areas.[51,58−60] While the dimensions of EJ change across location and time, vulnerable populations are frequently exposed to higher levels of environmental risks.

ACCESSIBLE REVIEW AND FRAMEWORK FOR DIVERSE STAKEHOLDERS

This critial review proposes a guidance framework for selecting between common and emerging data analytic and modeling methods for estimating air pollution concentrations in EJ analysis, given the purpose of analysis, users, and resources available. The guidance framework seeks to aid in method selection for estimating air pollution concentrations in EJ studies and does not intend to serve as a comprehensive framework for conducting EJ research. The framework is intended to formalize the way many experienced researchers instinctively approach questions of air pollution and environ-

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mental injustice and the trade-offs they consider in the method selection process. As a critical review, we focus on methods commonly used in EJ studies, not an exhaustive list of all methods applied to EJ analysis. Many other reviews have addressed evidence for the existence of environmental injustice concerns relating to air pollution.[17,61] Some reviews focus on EJ concerns resulting from a particular industry, such as oil and gas.[19] Other reviews that study methods used in EJ research characterize EJ methods more broadly[62] or consider specific exposure pathways (i.e., indoor exposure).[63] This critical review presents a focused study of methods used to create exposure estimates in EJ research, which includes incorporating new methods such as machine learning and reduced complexity models, as well as emphasizing a more community-based perspective. The critical review focuses mainly on methods to create exposure estimates from outdoor pollution, although indoor pollution, and its influences on personal exposure, is also considered.

Environmental justice studies can differ from other air quality research in many ways. Two of the most prominent ways may be the level of community interest and the diverse set of stakeholders that are concerned with the process and outcome of EJ studies.[50,64−69] As a result, EJ research often demands an interdisciplinary and transdisciplinary perspective, which can strengthen the scholarship while also potentially leading to challenges such as misunderstandings due to language differences between disciplines and partners.[70−73] EJ researchers frequently identify the policy implications of their work, as demand for science-based policy has become more prevalent.[58,74] Interpretability, in this case the ability to distinguish what influences concentration estimates, can be more heavily emphasized in some EJ studies.[75−78] This highlights the complex relationship between the existence of environmental hazards, exposure, difficult to quantify environmental impacts, and socioeconomic dimensions within EJ scholarship. The need to identify vulnerable communities can seem to be in tension with taking care to avoid misrecognition or labeling a place as harmful or degraded, which may lead to the stigmatization of communities or unfair blaming of community residents.[49] Indeed, air pollution concerns in EJ communities often go beyond the health effects associated with air pollution and additionally include noise, odor, and quality of life.[78−81] This range of effects necessitates a suite of methods to assess exposure. Often, researchers use outdoor concentration as a proxy for personal exposure, even though this measure may not be representative of how complex personal exposure can be, as people constantly move through microenvironments (Figure 1). In other cases, simple methods such as distance from a source are used, which may not capture air pollution exposure as well but might improve consideration of other effects of living close to a source. Finally, an important difference between EJ studies and other air pollution studies is the importance of scale. Many EJ projects focus on communities and neighborhoods, and it is vital for the studies to be able to differentiate between concentration estimates within that space. Due to these differences, EJ studies may have unique requirements for methods compared to other air pollution analyses.

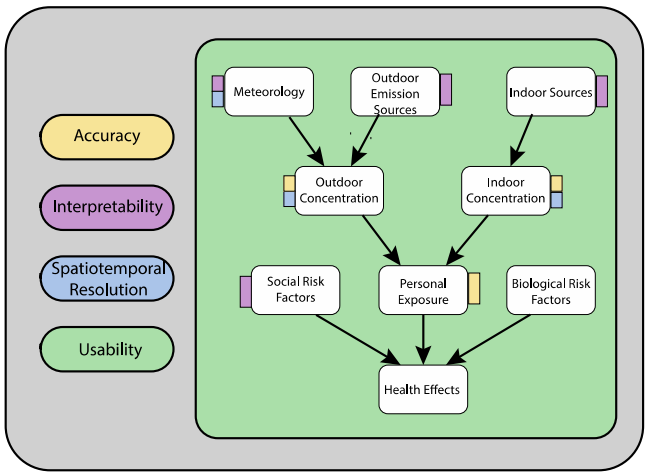

Figure 1. This figure illustrates how major environmental and human factors ultimately influence human health effects of air pollution. The color boxes within the flowchart represent corresponding elements of the framework for consideration. See Figure 2 for an explanation of the framework tenets: accuracy, interpretability, spatiotemporal resolution, and usability.

■ REVIEW OF COMMON MODELING AND DATA ANALYTIC TECHNIQUES TO CREATE CONCENTRATION ESTIMATES FOR EJ ANALYSIS

To conduct the scoping review, we searched Google Scholar, PubMed, Web of Science, and other indexes and databases available through the University of British Columbia.[82] Keywords for our search included "environmental justice", "modeling", "analysis", and "air pollution", as well as search terms specific to different methods upon review of initial findings (e.g., "dispersion model" AND "environmental justice"). Our aim in this critical review was to capture the diversity of methods in the field. We constrained our key citations to fall within the past 20 years, with a focus on novel and emerging methods. Many types of exposure estimation methods are regularly applied to EJ analysis, often with the goal to identify connections between exposure disparities and sociodemographic vulnerability. The most used are explored in this section. There are many useful ways to classify methods; however, the categorization most relevant to this critical review is by the concentration or exposure estimation process they employ. Our categorization attempts to clarify distinctions among methods and how they are commonly used but is not meant to constrain possible use cases. There is latitude within categories and individual methods which is further explored in Table 1, while the text below is meant to illustrate the most common EJ applications observed in the literature.

Proxy Methods. Some of the oldest and most frequently used methods in the EJ field are proxy methods. Proxy methods approximate the hazards of air pollution at a location by focusing on factors that are upstream of pollutant concentration and exposure in the causal impact chain—most often the location or amount of emissions. It should be noted that ambient concentration, often at the place of residence, is itself used as a proxy for exposure in many air pollution and EJ studies, even though we elaborate on ambient concentration estimation methods separately in subsequent sections. Methods that utilize source location or emissions to create a proxy estimate for concentration are detailed below.

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Table 1. Summary of Methods Commonly Used in Environmental Justice Analysis[a]

			How has it been used?				Why is it used?			
	Method	Common Applications	Data Requirements	Spatial Scale	Temporal Scale	Common Pollutants	Accuracy	Interpretability	Usability	Key Examples
Proxy Methods	UHC	PD	Location of hazards, sometimes emissions	Regional-National	Yearly or longer - data does not change quickly	HAPs	Low - Low concentration accuracy but can capture other detrimental effects from environmental hazards	Medium - Can pinpoint where the hazards are but their area of impact may be mischaracterized	High - Highly useable with easily accessible data	8, 15, 16, 23, 36, 38, 48
	Proximity Analysis	PD	Location of hazards, sometimes emissions	Local-National	Yearly or longer - data does not change quickly	HAPs or TRAPs	Low - Low concentration accuracy but can capture other detrimental effects from environmental hazards	Medium - Can pinpoint where the hazards are but their area of impact may be mischaracterized (though to a potentially lesser extent than UHC)	High - Highly useable with easily accessible data	3, 4, 7, 9, 13, 15, 20, 26, 30, 49
Monitor-Based Methods	Personal Exposure	PD, H	Monitoring from wearable monitors or stationary microenvironment monitors	Hyperlocal	Short term	HAPs or TRAPs	High - Highly accurate concentration estimation of what a person actually breathes	Medium - Can be highly accurate depending on study design but may not be generalizable to larger populations	Low - Personal or microenvironment monitoring can be costly and difficult to organize	10, 11, 17, 29, 47, 50
	Interpolation	PD	Stationary or mobile monitor	Local-Regional	Short term to yearly or longer	Criteria pollutants	Medium - Dependent on the availability of data but can capture relevant statistics (mean, standard deviation) of concentrations	Low - It may not be clear what is influencing concentrations without further data analysis	High - Highly useable with easily accessible data	11, 19, 35
	Satellite Data	PD	Satellite	Regional-National	Short term to yearly or longer	PM, O_3	Medium - Dependent on meteorological conditions	Low - It may not be clear what is influencing concentrations without further data analysis	Low - Data may be more difficult to access and the format may be challenging	51, 52
Statistical Methods	Kriging Interpolation	PD	Stationary or mobile monitor	Local-Regional	Short term to yearly or longer	Criteria pollutants	Medium - Dependent on data availability but generally estimates concentrations well due to consideration of spatial autocorrelation	Low - It may not be clear what is influencing concentrations without further data analysis	High - Highly useable with easily accessible data	1, 5, 44
	LUR	PD	Stationary or mobile monitor, geographic variables	Local-Regional	Yearly or longer - data does not change quickly	Criteria pollutants, TRAPs	Medium - Dependent on the availability of concentration and geographic data	High - Ability to see which variables are most significant in the model	High - Highly useable with easily accessible data as geographic variables are often easy to obtain	11, 22, 31, 37, 41
	Emerging Models	PD	Stationary or mobile monitor, geographic variables, meteorological, or others	Local-Regional	Moderate length - yearly	Criteria pollutants	Medium - Dependent on the availability of data and user experience	Low - It may not be clear how all variables affect concentrations and ability to extrapolate is low	Low - Method is complex, success is highly dependent on data inputs and user experience	45
Process-Based Methods	Dispersion Models	PD, H, E, FS	Emissions from point, line, or area source(s), meteorological	Local-Regional	Short term to yearly or longer	Range of non-reactive aerosols and gases	High – Concentration can be highly accurate (especially more complex models) due to consideration of meteorology	Medium - Can be interpretable through what-if analyses	Medium - Easy to use for modeling with some simple options available but can get more complicated	2, 18, 25, 28, 34,
	CTM/RCM	PD, H, E, FS	Emissions from point, line, or area source(s), meteorological	Local-National	Short term to yearly or longer	Any health-relevant aerosol or gas	High – Concentration can be highly accurate (especially more complex models) due to consideration of meteorology	Medium - Can be interpretable through what-if analyses	Low - Method is complex and requires modeling expertise	8, 40, 42, 43, 46, 53

[a]Pattern description (PD): Captures air pollution patterns related to sociodemographic variables. Health (H): Connects concentrations with health risk or outcomes. Explanation (E): Focus on more interpretation—what affects concentrations and why. Future Scenario (FS): What-if analysis. *Key Examples* study numbers are from Table S1, which is available in the SI. Examples of PD, H, E, and FS research questions are also provided in the SI.

Unit-Hazard Coincidence. Arguably the most common proxy method in EJ research is Unit-Hazard Coincidence (UHC). UHC identifies the number of hazards within a geographic boundary and uses that as a basis to compare different communities defined by their unique sociodemographic characteristics. This method was employed by the first major US EJ study on air pollution.[83] Since then, it continues to be used as a simple and widely recognized means of capturing the detrimental effects of living close to environmental hazards.[42,84−88] UHC is typically used in studies concerned with hazardous air pollutants (HAPs) from industrial sources or other point source pollution. Toxic release locations are often the input data of proxy methods because of the detrimental health effects of living close to industry and infrastructure.

UHC's main advantages are that it is easy to use and understand. As a result, it can be of special interest to practitioners. UHC can be necessary in cases where there are no monitor data, as is common for many HAPs from industrial facilities, or validated modeling frameworks, which require an observational data set to evaluate performance. One of the main limitations of UHC is potentially obscuring the spatial relationship between a hazard and the population it affects. A hazard categorized as located within one spatial unit may affect a population living in another spatial unit due to location within the area (i.e., on the border) or atmospheric transport.[84] Another limitation is the focus on primary pollutants. Finally, UHC can be unstandardized between studies, with different geographical areas and hazards studied, which is of particular concern for transferability and interpretability of results.

There are a variety of ways to extend the UHC method. Previous EJ studies have used Ripley's K,[89] Gini coefficient,[90] spatial cluster analysis,[91,92] and toxicity weighted aggregate levels[53] to assess inequality from emissions locations or emissions data as aggregated within geographic boundaries. This collection of examples contains only some of the extensions that have been used in EJ research, with the potential for many others.

Proximity Analysis. Proximity analysis is another common approach to approximate pollution exposure in EJ studies. This method uses the location of a hazard and overlays a buffer around the hazard to define "exposed" and "unexposed" areas.

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Buffer size depends on both the type of hazard and type of pollutant being studied. Proximity analysis is mainly used in EJ research to study the influence of toxic releases of HAPs or other industrial pollutants, roadways, and other infrastructure.[85,93−100] Proximity analysis is also used as one variable in some screening methods (see section "EJ Community Identification" in the Supporting Information (SI) for more on screening methods) due to its simplicity and wide applicability to a number of hazards.[101]

The strongest advantages of proximity analysis are that it is simple to use and can capture other detrimental effects of living close to environmental hazards (e.g., property values). However, it does not directly define concentrations or exposure to pollution. Compared to a similar method, UHC, proximity analysis may capture the area that is influenced by environmental hazards more accurately but can also be more difficult to perform, as the user is defining geographic boundaries instead of using ones that are predetermined (e.g., units of political administration, such as counties) and must adjust sociodemographic data accordingly.

Monitor-Based Methods. Monitor-based methods are characterized by their use of monitoring data to create a concentration estimate. A wide variety of monitors are used in air pollution research and are also applied to EJ analysis, including regulatory monitors, other stationary monitors, mobile monitors, wearable monitors, low-cost sensors, and satellite-borne instruments. Although these monitors are often operated by government authorities or academic research institutions, communities impacted by air pollution are increasingly conducting their own monitoring studies or partnering with researchers and governments to do so. Local air quality data, such as that collected by community bucket sampling (a low-cost form of sampling that captures a snapshot of air quality at a point in time), can potentially better inform personal exposure estimates.[67] Residents or researchers can more readily deploy low-cost sensors than research grade monitors for common pollutants.[102] The role of community monitoring and community engaged research in collecting observational data on air pollution for EJ research is addressed further in the Usability section.

Personal Exposure. A person's exposure to air pollution can be highly unique and individual as people move through microenvironments in their daily life. Personal exposure methods aim to estimate what people actually breathe as closely as possible. Often this is done using a wearable monitor or by placing a stationary monitor where people spend the most time, such as at home or at work.[79,103−108] Because this kind of monitoring requires engagement with individuals in the community of interest, personal exposure studies can be well suited to EJ communities which may already be organized and active in the air pollution space. Within EJ research, personal exposure has mainly been used in studies concerned with health effects[103,109] and in studies comparing personal exposures of different predefined populations.[106,108] Personal exposure monitoring is not as common as other monitor-based methods due to a large number of challenges with the method.

Wearable monitors are constrained to pollutants that have portable instrumentation. On the other hand, home or work monitoring can be performed for a wide range of pollutants, from particulate matter to HAPs. Personal exposure monitoring can provide more emphasis on indoor air pollution, where many people spend the majority of their time, and can provide a highly accurate picture of what the monitored person actually breathes.[110] The limitation with employing widespread use of personal monitoring is that it can be challenging to access enough resources to obtain a comprehensive data set. Additionally, EJ questions tend to be on the community scale, given interest in the relationship between social stratification and pollution exposure. Collecting sufficient personal exposure data to elucidate relationships to sociodemographic characteristics may be challenging in some cases.

Interpolation. Interpolation is a collection of methods that solely utilize monitor data. Different interpolation methods weight data differently, but as they are defined in this paper, they all use arithmetic processing to estimate concentration.[111] A wide range of pollutants can be evaluated using interpolation, but criteria pollutants (PM (including BC), O_3, NO_2, among others) are the most frequent due to the existing regulatory monitoring network and their health relevance. Some interpolation methods may be more appropriate for regulatory monitoring, other forms of stationary monitoring, or mobile monitoring than others. Common interpolation methods include buffer (averages all monitors within a certain distance from a receptor),[101] inverse distance weighting (inverse distance weighted average of all monitors within a selected area),[107,112] and spline (interpolates between monitors to minimize the curvature of the surface and is best for gently varying surfaces).[76] These basic interpolation methods are not frequently used within EJ research due to the large spatial gaps that exist in many monitoring networks. However, the same principles of the buffer method can be applied to other measures, where examples include the number of Toxic Release Inventory (TRI) sites[98] or estimated roadway emissions[99] within a buffer from an identified receptor.

Interpolation is one of the simplest methods available for creating a surface of absolute concentration estimates and may be able to capture similar statistics, including mean, median, and standard deviation, to more complicated methods such as land use regression or chemical transport models.[113] Because of its simplicity, few resources are required for the analysis. Although interpolation can have many advantages, the availability of data is key to being able to capture finer scale details in the concentration surface, and it may still miss localized areas of elevated pollution. Regulatory monitors are generally sited to ensure regulatory compliance, and other stationary monitors may aim to capture background concentrations instead of pollution variations. Additionally, the quality of the estimation relies heavily on the quality of data. Low-cost or mobile monitoring may require intensive data processing steps before interpolation that significantly decrease ease of use.

Satellite Remote Sensing. Satellite-borne instruments are a relatively new means of measuring surface air pollution. Their readings of optical depth and other spectral measurements can be used to estimate pollutant concentrations, although this is nontrivial due to the intensity of the process and the number of methods that can be used.[114,115] Concentrations of PM, O_3, CH_4, CO, SO_2, and NO_x can be derived from satellite-based measurements, depending on the instrumentation.[114,116,117] Within EJ research, satellite data have been used to detect industrial flaring or the burning of unwanted gases[81] and for estimating long-term concentrations within a large study area (the US state of Louisiana).[24] There have also been applications at a finer spatial scale; Demetillo et al. demonstrated the ability of the Tropospheric Monitoring Instrument (TROPOMI) to resolve relative NO_2 concen-

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tration differences at the US census tract level.[114] The authors take into account the impacts of retrieval biases and time averaging and relationships between spatial patterns in the atmospheric column versus those at the surface.[114] Most of the applications of satellite data to EJ have been quite recent, and while there is not a large body of work on the method currently, increasing spatial resolution, range of pollutants considered, and accessibility of processed remote sensing data products will likely bring increased use.

Satellite data can be used as input for other methods, taking advantage of the large geographic areas that can be covered.[118,119] A strength of satellite data is relatively consistent coverage of large spatial areas, including many areas that may not have regulatory monitoring networks. Satellite data have recently been shown to be able to accurately estimate $PM_{2.5}$ and NO_2 concentrations on a small spatial scale and capture spatial variability, which is important in many EJ analyses.[114,120,121] However, satellites have not yet been used to measure many pollutants of EJ concern, including HAPs, given the limits of optical measurement techniques. Satellites collect data on the total atmospheric column which can make converting instrument measurements to pollutant concentrations at the surface challenging, especially for long-lived pollutants or pollutants such as ozone that are elevated at high altitudes. Satellites can present issues with temporal coverage gaps, as many satellites measure once a day at a given location.[115]

Statistical Methods. The statistical methods discussed in this section treat sampling data from monitors as realizations of a random variable in producing spatial and temporal concentration estimates. These methods therefore allow for consideration of relationships between variables (e.g., correlation) and uncertainty quantification in inferring out-of-sample locations and times.

Kriging Interpolation (KI). While KI is a form of interpolation, it differs from the methods described above in that it involves more advanced geostatistical techniques (assuming a Gaussian process) and is used quite frequently in air pollution studies, meriting its own category. KI employs the use of autocorrelation or the concept that samples are not completely independent. This method still only requires monitor data but can potentially increase accuracy in concentration estimates. KI has been used extensively in the EJ literature because it is quite easy to implement with modern geographic information system programs and geospatial packages. Many EJ studies have used it as a means to process monitor data into an exposure surface to connect to sociodemographic variables[75,122−124] and in some cases extend the analysis to health impacts.[125,126]

Much of this advantage comes from the method's consideration of spatial autocorrelation when creating estimates. KI gives the best results when measurements are correlated between different monitoring stations, which is most likely to occur when there is a sufficiently dense network. This can be difficult to achieve in some areas of interest for EJ research.

Land Use Regression (LUR). LUR relates land use variables with monitored data to create a better estimate of air pollution concentrations. This model is best applied to pollutants that are related to land use, such as traffic-related air pollutants (TRAP). Since many of these pollutants are of particular concern for EJ communities, LUR is often used in urban or regional EJ studies.[107,127,128] However, LURs have also been applied to EJ at a national level for selected urban areas within a country[119] and both urban and rural areas together.[118] LURs have mainly been used for NO_2,[118,119,128] $PM_{2.5}$,[127] and BC,[127] as these pollutants are strongly associated with land use.

LUR has advantages over many purely monitor-based methods because it is still fairly simple to use and is well tested; however, it can improve the accuracy of concentration estimates at finer spatial scales and is adaptable to many monitoring schemes. On the other hand, LUR requires access to geospatial variables which may be difficult to find for some areas. The method is also only applicable to pollutants related to land use. Many geospatial data sets have resolutions that are high enough to support the application of LURs to intraurban analysis but may prove to be a challenge in a large regional or nationwide application. Additionally, this approach does not explicitly represent atmospheric processes and relies on statistical relationships between geospatial variables and monitored air pollution to predict concentrations at other locations. However, spatial patterns of secondary pollutants may still be coupled with land use patterns and can be well predicted with an LUR.[129]

Emerging Models. Emerging models are categorized as advanced statistical techniques. The most widely applied of the suite of emerging techniques is machine learning (ML). ML differs from statistics in that it finds generalizable patterns, while statistics focuses on inferences from a specific population.[130] There are many types of ML models, including random forests, boosted trees, and linear support vector machines. Emerging models have historically been used mainly for PM or other criteria pollutants, air quality indices (AQI), and other cumulative measures of air pollution.[131,132] Emerging models are increasingly applied in atmospheric sciences and air quality in particular with the proliferation of large data sets. Applications for EJ questions have still been infrequent to date due to the relative novelty of these methods. One study applied ML to research the integration of nonregulatory monitors with satellite measurements to obtain accurate, neighborhood-level concentration estimates of $PM_{2.5}$ for EJ analysis.[133] In another study, deep neural networks were used to identify videos with industrial smoke events taken by community members, for the purpose of taking regulatory action.[129]

ML can be used to identify and utilize patterns in a manner beyond human capabilities.[120] Besides being able to use much larger data sets, new forms of data are becoming increasingly common in ML within the air pollution field, such as image and video analysis, which have previously been too resource intensive to analyze in a standardized manner.[120,133,134] ML also provides the possibility for increasingly accurate concentration estimations. Some disadvantages of ML may be particularly strong for EJ analysis however, as the process is more opaque than others, and the results are less interpretable and can be difficult to analyze.[135] ML can have trouble handling out-of-sample modeling, although this can be mitigated through validation approaches (i.e., k-fold cross-validation).[136] Additionally, ML has not been as widely applied to EJ analysis as other methods, possibly due to its complexity and relative novelty.

Process-Based Methods. Many common methods for estimating air pollution concentrations model atmospheric processes (advection, diffusion, and chemical reactions) to approximate the fate and transport of air pollution emissions.

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Dispersion Models. Any model that relies primarily on atmospheric advection−diffusion equations with little atmospheric chemistry is considered a dispersion model. Dispersion models are highly useful for EJ studies because they can model many pollutants, both aerosols and gases, as long as they are not highly chemically reactive.[76,89,93,137−140] There are many examples of dispersion models, but they generally range from simple models that focus on a few point or line sources such as roads (i.e., CALINE, COPERT) to models that are more complex, include more sources, and rely on more complete meteorological data (i.e., AERMOD, CALPUFF). Many of the more complex models can include simplified atmospheric chemistry but are still not appropriate for some reactive air pollutant species. Within EJ, dispersion models are commonly used for estimating EJ impacts of traffic emissions, for example, the influence of vehicle emissions on schoolchildren.[140] Dispersion models are also often required for regulatory permitting, where community activists may be engaged with the process.[141]

Dispersion models are simpler and easier to understand than some more complex models, partially because they are most applicable to point or line sources and tend to focus on one source at a time. This makes them highly useful for investigating the impact of one or a handful of sources (such as within the permitting process) but limits the ability of a study to analyze many sources and their cumulative impact. In addition, they are based on approximating real-life atmospheric conditions. Nonetheless, they are more challenging to use and understand than simpler methods and require emissions data, which may be more difficult to access than monitoring data.

Chemical Transport Models (CTMs) and Reduced Complexity Models (RCMs). Often considered the gold standard for air quality modeling, CTMs simulate atmospheric conditions and solve the continuity equation (mass conservation) for chemical species of interest, given emissions and meteorological data.[142] A wide range of pollutants can be represented with CTMs, as they have the capability to model many phenomena, including chemical reactions between pollutants and photochemistry. However, within EJ research, CTMs are most commonly used to model $PM_{2.5}$,[75,79,143−145] NO_x,[79,143] and O_3.[145−147] A more accessible version of CTMs are RCMs, which use various techniques to reduce computational complexity and are gaining traction in EJ analyses.[148] These techniques include (but are not limited to) simplified representations of chemistry, response surface models, regression models based on large numbers of CTM simulations with small emissions perturbations, and the development of source-receptor matrices.[148] While CTMs are often used for many different air pollutants, RCMs usually focus on $PM_{2.5}$, as it is a major health concern and is well adapted to the simplified nature of RCMs. Both CTMs and RCMs are frequently used in air pollution studies and are utilized in EJ studies for a range of spatial domains, from city level to nationwide.[75,79,143,144,147,149]

CTMs can be useful for simulating atmospheric concentrations over large 3D-spatial and temporal domains in a consistent manner, enabling large scale analysis. CTMs can be difficult to learn and computationally expensive. The spatial resolution of some CTMs, often constrained by input data resolution, may be too large to be appropriate for many EJ analyses. Other CTMs, such as CMAQ (Community Multiscale Air Quality Model), use adaptive grids or nesting to achieve finer spatial resolution at locations where resolution is important. However, obtaining emissions and meteorological data at a fine scale (i.e., to capture intraurban variability) can be challenging. Many of the disadvantages of CTMs can be somewhat mitigated by using RCMs if appropriate to the study goals. Due to their reduced complexity, RCMs are less computationally intense and can be more readily used for sensitivity analysis, Monte Carlo simulations, or longer studies.

Hybrid Methods. Hybrid methods are commonly used to mitigate the trade-offs between different methods (i.e., between computational intensity and accuracy of concentration estimates). All the methods outlined above can be used individually, but many have significant disadvantages. A combined method can be a stronger choice. Care should be taken to ensure that all the methods being combined are appropriate for the pollutant of interest. Hybrid methods are fairly commonly used in EJ analysis. Some examples of hybrid methods used in past EJ studies include interpolation and CTM,[75] interpolation and dispersion modeling,[76,150] and CTM with a downscaler model.[145] Since EJ studies may have limited resources while desiring some of the benefits of modeling for future scenario analysis, hybrid models can be a good choice. Overall, thoughtful combinations of methods can strengthen the advantages of each method while minimizing the disadvantages.

■ PROPOSED CONCEPTUAL GUIDANCE FRAMEWORK

Drawing on our review of concentration/exposure estimation methods applied to EJ research, we propose a framework for selecting between different methods given the purpose, users, and resources available. As such, we aim to answer the questions "what methods would be appropriate for common study types?" and "what do we need and what do we want from a method to support EJ communities?" Trade-offs between methods exist with each aspect and are explored in the framework below. For example, higher accuracy in concentration estimates may necessitate higher spatial resolution. The framework addresses these concerns and provides guidance on how to critically evaluate a wide range of methods. The goal is not to identify a method that performs best for each criterion but rather to use the criteria of the framework to find the method that fits best with the research question—this may mean larger emphasis on some criteria than others. The value added by implementing the guidance framework is the time, money, or other resources (within communities and research teams) saved by formalizing research design decisions and selecting fit-for-purpose methods. We expand on the utility of this kind of structured method selection approach in the Application of the Framework to Selected Case Studies section. We visualize the framework in Figure 2.

Accuracy. In a traditional sense, accuracy in air pollution studies refers to how close an estimated concentration is to the actual value. Related concepts include data precision, which is related to statistical variability, and sensor selectivity (i.e., measurement cross-sensitivities). Accuracy in concentration estimates can be important for understanding the scale of distributional patterns, particularly against external benchmarks such as regulatory standards or health-based guidelines. Accuracy of concentration estimates is also useful for drawing linkages to health effects and health-related disparities, particularly when combined with other data sets such as movement data, yielding improved personal exposure estimates. Further, many existing epidemiological relationships

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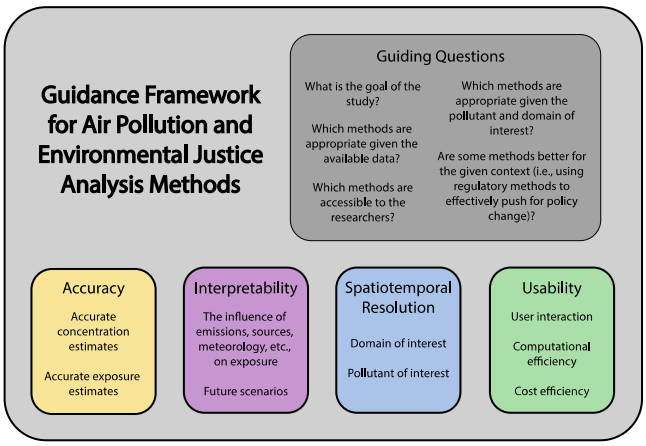

Figure 2. This figure summarizes the key points of the guidance framework for method evaluation for use in EJ analysis and a selection of questions to consider while reviewing the framework's tenants.

suggest nonlinear responses between pollutant concentrations at the place of residence (as a proxy for personal exposure) and adverse health impacts.[35,36,38,39] Consequently, accuracy in concentration estimates is important for assessing the potential health impacts of EJ interventions, as the same change in concentration may result in different magnitudes of health response, depending on the starting point.[151] Finally, improving accuracy across multiple pollutants will help to address the challenges of estimating cumulative health effects. However, EJ studies present a unique set of considerations for concentration accuracy. A chosen method may accurately estimate concentrations but may not be appropriate for the desired spatial or temporal resolution, especially as some EJ research focuses on a neighborhood level. Additionally, some methods are better suited to accurately estimate certain pollutants, which may not always correspond to the most health-relevant pollutants that concern EJ communities. To ensure that concentration estimates are accurate, they are often checked against validated observational data for the same location and time period. The accuracy of the monitor data is dependent on instrumentation and measurement techniques. Checks on model accuracy can be difficult in areas that have few monitors, which may include EJ communities with limited resources and representation. When methods rely on monitored data, such as KI, areas with few monitors can have large standard errors.[122] However, only considering areas with sufficient monitors can lead to bias.[86] The monitors themselves can add to uncertainty through measurement selectivity or consistent biases. For example, conventional NO_2 monitors tend to overestimate concentrations, especially during hotter weather due to photochemistry.[152] Others, especially low-cost sensors, may by prone to cross-sensitivities.[153] Accurately estimating concentrations is simply one aspect of studying the environment in relation to sociodemographic variables, and often the methods best for concentration accuracy do not measure other related phenomena, such as reduced land value.

The idea of accuracy also has other facets in the context of EJ research. At times, EJ studies may be more concerned with precisely estimating relative pollutant concentrations than absolute concentrations. One case where relative pollutant concentrations are of primary concern is in the identification of pollution hotspots.[154] If the chosen method is precise but not accurate, the identification of hotspots would still give valuable information on which neighborhoods are relatively more exposed. When the main interest is relative concentrations, the range of available methods is expanded, as differences in means and standard deviations of annual average estimates at small geographical units among interpolation methods, proximity analysis, LUR, and some CTMs are potentially small.[113] Methods that do not estimate absolute pollution concentrations accurately could be used for EJ analysis with potential advantages of simplicity and ease of use.

Interpretability. Interpretability is a broad concept that is defined in this critical review as focusing on the ability to identify drivers of observed concentrations (e.g., sources, land use patterns, meteorology, or other factors). Interpretability can be of interest in general air pollution studies but may be of particular concern in some EJ research. To move beyond identifying EJ communities and toward creating evidence-based policy, interpretability can be vital to informing targeted action. Interpretability is a continuum and may depend on how a method is used (e.g., used within data set or out of data set). Interpretability can aid in taking the research further and advocating for change. Some methods produce more interpretable results than others, with regression modeling techniques such as LUR being highly interpretable due to the ability to determine which variables influence the concentrations. For example, Messier et al. constructed an LUR where geographic variables were only added when they increased the model R^2.[155] Knowledge of factors affecting concentrations, such as road density, could inform transportation planning decisions on the distribution of roads within a community or siting decisions around the location of a new affordable housing project or a school. Factors identified as being key drivers of air pollution concentration can also then be linked to more structural upstream drivers of pollution-related inequities, such as environmental racism in zoning.[156] Complex techniques such as dispersion modeling, RCMs, CTMs, or novel methods can offer high levels of interpretability through assessment of what-if scenarios. They connect sources and meteorology to concentrations, and alternative scenarios can be compared to provide insight into the influence of different model inputs. Cases where sources are changing are used to represent the opening or closing of industrial facilities,[157,158] the impact of human activities,[149] and changing infrastructure development strategies.[75,76] The ability to change meteorological inputs is key to studying future climate scenarios. Communities often advocate for specific policies or practices, and researchers can support their arguments through what-if scenario analysis. On the opposite end of the interpretability spectrum, monitor-based methods may offer little. Although monitor data may be less influenced by a priori assumptions, using this data to tease out potential influences on concentrations typically requires using additional data as well, whether this be combining sensor data with local knowledge, conducting source apportionment analysis that may require more comprehensive suites of measurement, or implementing a back trajectory analysis to understand the impact of sources and meteorology. The interpretability of all methods is bounded by the spatiotemporal resolution and uncertainty in input data sets, as all monitoring and environmental data have inherent limitations. Some methods, such as CTMs, may be better suited to uncertainty analysis where users systematically characterize the influence of uncertainty in inputs on outputs. Method implementation

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decisions can also affect interpretability. As an example, novel methods are complex, and their ability to extrapolate out of their training set is highly dependent on how the model is built. Monitor-based methods that rely only on measured data may offer limited insight into what affects concentrations in most cases. Depending on the purpose of the study, the need for interpretability can severely constrain method selection.

Spatiotemporal Resolution. Within this framework, spatiotemporal resolution considers the resolution and domain of the data, of the method, and of study interest.

Spatial Resolution. The study question and available data should inform the spatial resolution of a chosen method. Spatial resolution can be of particular importance in EJ studies and presents unique challenges. Many EJ studies aim to conduct research at spatial scales where disparities are most visible, usually at a neighborhood level. However, it can be difficult to access neighborhood level data, and as a result, spatial resolution can be constrained by the resolution of sociodemographic data. Health analyses are often limited by the spatial resolution of health data sets as well. For many reasons, including the sensitive nature of the data, health data are often not available at urban or intraurban levels, although it is important to identify health effects for different sociodemographic groups.[47,159] EJ analyses are often conducted at census tract,[86,101,122,123,137,145] zip code,[147] and census block[118,138] levels as publicly available sociodemographic data are reported in these units.

While it may not always be possible, EJ researchers frequently desire relatively high spatial resolution to be able to identify EJ communities. One issue that arises when resolution is an input for a modeling method is that the accuracy of the estimated exposure is different with different resolutions.[160] In some cases, the ideal study would be able to estimate personal exposure for every individual to obtain the smallest possible socio-spatial resolution.[62] The desire for small spatial resolution is at times in tension with the need to analyze large spatial areas for some EJ studies. Regions of particular EJ interest can be quite large, and national-level studies can provide useful information for large scale EJ patterns, especially when research is just beginning in many countries.[42,53,161]

Challenges with analyzing large spatial domains arise across the spectrum of available methods. With modeling, large spatial domains may have swaths of land that are less populous (i.e., rural or industrial areas) which may be necessary to include but could require significant computational resources. Often, EJ is thought of as an urban issue since many sources of air pollution are located in and around cities and towns. However, this is not always the case, and rural communities may experience EJ issues surrounding animal agriculture[138] and industrial emissions,[81] while facing a lack of monitoring.[11] Some of the simplest methods rely on monitor data, and regulatory monitoring networks can be sparse or unstandardized among different governmental areas.

EJ pollutants of interest differ in their spatial variation due to intrinsic pollutant characteristics. For example, $PM_{2.5}$ is both a primary pollutant and secondary pollutant and is considered in many EJ studies due to its health relevance. In one study, secondary $PM_{2.5}$ showed less spatial variation than O_3 in most Canadian cities considered, while O_3 in turn exhibited less spatial variation than primary $PM_{2.5}$.[162] Spatial variations are a result of how a pollutant is emitted as well as fate and transport. Pollutants may be mainly emitted from point sources such as industrial facilities,[94] line sources such as roads,[163] or area sources such as concentrated animal feeding operations.[138] As a result, methods to accurately capture their effects may be different. In addition, it is important to recognize the nonlinearity and spatiality of EJ community identification.[93]

One general challenge with air pollution studies is the modifiable unit area problem or when changing the spatial resolution of the method changes the outcome of the analysis.[62,117] This can be a significant issue in EJ research, especially if a unit of analysis is too large and mischaracterizes EJ patterns. A concern for many air pollution studies is the ability to capture the differences between emissions and impacts. In the case of EJ research, this means identifying where an environmental hazard is being produced and the space or pathways through which it impacts people and communities.[49,164] Different methods are commonly applied at different spatial scales. Interpolation methods and some complex modeling methods are generally better at reflecting urban scale differences, while LURs are used for capturing neighborhood-scale pollutant concentration differences.[113] The influence of spatial domains on method selection must be considered as well. One common problem that can arise in any spatial study is the edge effect problem, where the results at the edges of the study domain are less reliable due to the abrupt transition between an area with data to an area without.[93] This can be mitigated within modeling methods by using a buffer around the domain of interest, but it is harder to account for with methods that rely on monitoring data.

Temporal Resolution. Similar to spatial variability, characteristics of a pollutant can influence its temporal variability. For example, primary pollutants can vary at smaller temporal scales than secondary pollutants. Oxidation and other chemical processes greatly affect the temporal variability of short-lived, reactive trace gases.[114] Temporal variability of pollutants also depends on natural variability from diurnal and seasonal variations due to changing boundary layer height and meteorology, as well as the source of the pollutant. As an example, NO_2 can simultaneously exhibit diurnal variability as a traffic-related pollutant and seasonal variability due to its photochemistry.[114,165,166] At other times, industry or heavily emitting mobile sources can emit large amounts of HAPs at once, resulting in a sharp spike in emissions and concentrations. These acute events are of interest to fenceline communities (communities proximate to sources).[167] However, this occurs at a fine temporal scale, and spikes in emissions have a shorter period of influence on concentrations than continuous or more frequent intermittent sources. The best method for an EJ analysis depends on the appropriate temporal resolution for the question in addition to pollutant considerations. EJ and health effects studies are most often interested in long-term health effects, such as cancer risk,[137] cardiovascular disease,[168] and mortality,[126] in which case longer averaging periods for concentrations can be acceptable. A smaller number focus on acute effects, such as asthma hospitalizations or cardiac arrests, which are still often studied with high temporal averages within EJ literature although are frequently analyzed on finer temporal scales in the broader health and air pollution field.[94,147,169] Spatial methods and CTMs have strong potential to offer high temporal resolution, while methods such as LURs often use long-term concentration averages. For EJ analyses, it is vital to recognize the temporal scale of the research objective. Some communities may be most concerned about high baseline pollution levels

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from nearby sources, such as roads.[163] Others may want to investigate disproportionate exposure to short-term spikes in emissions, such as those from the practice of industrial flaring.[81]

Usability. An aspect of usability that may weigh more heavily for EJ studies than for other air pollution studies is the ease of use in research and decision making. This is due to the interdisciplinary nature of EJ research and strong action orientation. Methods that are simple yet accurately estimate concentrations at a fine temporal and spatial scale are rare. Air pollution researchers often have many complex methods at their disposal. In contrast, some researchers who are interested in EJ and want to use and understand air pollution estimation methods are not specialists in air pollution methods. Others, including practitioners, require methods that can be used by staff and fit within a project assessment timeline.[170] Another consideration is data sources, as researchers may be interested in methods where appropriate data are not easily obtainable. This could be due to limited public availability of data sets at the appropriate spatiotemporal resolution or the cost involved in gathering data. Methods that work well with low-cost sensors and other means of community monitoring data such as the previously described "buckets" can be highly useable due to affordability and creation of data where there otherwise are none.[67,171−174]

One reason for the special significance of usability in EJ research is that it frequently takes place in collaboration with a community and where one aim of the work may be to draw attention to air quality problems and spur regulatory action.[175−177] EJ research includes many studies where the scopes are focused on the local scale.[105,112,139] When this is the case, the chosen method should be appropriate for the main concerns of the community. If the community is interested in a certain pollutant, specific facility, cumulative effects, long-term exposure, or unpermitted releases, the method used should reflect those considerations. In addition, the best method for the research will reflect the available knowledge and data. Communities have deep knowledge about their environment, and some may have existing quantitative or qualitative data at their disposal.[141,178,179] As the results of community-based research are often used to advocate for policy changes, it can be advantageous when the study method is regarded as legitimate in government context.[67,173,180] For example, African American residents in Louisiana formed a bucket brigade to measure air toxics from a chemical plant adjacent to their community.[67] While the measurements spurred action to address toxic releases, the citizens' initiative challenged the standards of air quality monitoring but was ultimately unable to change how the government measures and, therefore, takes action to improve air quality.[67,173] Policy makers and decision makers may view a method that follows established standards as more valid and give greater credence to the results. Finally, when communities understand the methodological process that justifies their demands, they will more easily be able to use it to advocate for change. The method must also be understandable for those making decisions. Methods should incorporate all available community resources and be chosen to best serve community interests if community-based analysis is a central part of the research.

A strongly limiting factor is computational efficiency. It can be expensive to access computational resources, especially those required for some complex models such as CTMs. EJ questions that cover large areas may require a prohibitive level of computational resources.[75] This becomes even more significant if the question necessitates multiple analyses, such as those required for what-if scenarios. For example, testing the impact of closing select power plants requires multiple modeling runs.[158,181] The limitation of computational resources can be somewhat overcome by the use of hybrid methods that combine highly computationally expensive methods in a limited manner with a different, simple method.[75] Given the cost of computational resources, some methods may be out of reach for some researchers and study types.

The last aspect of usability is cost efficiency. This consideration can take many forms, including whether a method is open source or if it requires a license. Spatially based methods can be relatively simple with a high cost. These methods often use geospatial analysis programs, such as ArcGIS, which require licenses to use.[93,133,182,183] An open-source version of ArcGIS, QGIS, is available and used in EJ studies but may be less user friendly and decrease the ease of use for the method.[24,184] Other complex methods, such as CTMs, can necessitate specialized training. Even when a method can be self-taught, the number of paid hours that are required to become proficient can be prohibitive. Generally, faster and simpler analyses will cost less time and personpower.

■ APPLICATION OF THE FRAMEWORK TO SELECTED CASE STUDIES

When beginning a study, there are many questions and considerations to be weighed (Figure 2). The most important questions involve the goals of the study and how they advance environmental justice. Other concerns are the availability of resources, specifically the type, quantity, and quality of data available and the availability of expertise. The four criteria described above offer a structured way of exploring these different considerations and potential trade-offs. How each factor is weighted depends heavily on the context of the study—an appropriate method for a given research question does not need to perform well on all criteria. Further, understanding which of the four criteria are emphasized by a given study design can also inform the design of complementary studies. Below and in the SI, we provide selected examples of how different study goals and contexts may result in different methodological choices through application of the framework. These cases are inspired by past studies and our interpretation of their work. We consider cases of designing targeted interventions to reduce environmental injustice,[75] exposure assessment to support identification of air pollution related health disparities,[103] and developing screening methods for identifying communities experiencing environmental injustice considering cumulative impacts.[101] Here, we present the first case, with the other two provided in the SI.

Targeted Intervention. *What Is the Goal of the Study?* Policies that have the potential to result in a change in emissions are often of particular interest to EJ researchers and communities. Targeted intervention analysis can aid in identifying strategies to reduce existing injustices (e.g., identifying sources that drive inequitable exposures in EJ communities) or opposing policies/decisions that will exacerbate existing injustices. For example, in Nguyen and Marshall, researchers were interested in the question of where to place low-emission zones and truck reroutes to reduce inequitable exposure to diesel particulate matter.[75] They investigate disproportionalities in emissions, impacts, and

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distribution of harms or benefits using a hybrid method that combines CAMx (a CTM) and ordinary Kriging interpolation.

Which Methods Are Appropriate?

- Interpretability: Given the study goal, interpretability is a key consideration, and the what-if nature of this question necessitates an approach that allows for manipulation of input variables such that the effects of selected inputs can be distinguished. Here, this was the ability to link specific intervention design characteristics (spatial location of emissions reductions) to the resulting distribution of air pollution. Nguyen and Marshall chose to use CAMx (a CTM) to explore a range of possible scenarios by zeroing out emissions from traffic in one grid cell at a time.[75]
- Spatiotemporal resolution: The spatial resolution required to answer the question needs to be fine enough to distinguish changes in pollutant concentrations and exposure between sociodemographic groups but is also limited by the model resolution and sociodemographic data resolution (in this case, census block groups). Similarly, the temporal resolution must be high enough to distinguish diurnal patterns while considering modeling limitations and computational resources. In this case, the researchers chose a 2 km × 2 km spatial resolution and 1 h temporal resolution to capture changes in diesel particulate matter concentrations, exposure, and exposure disparity from implementing changes to diesel truck traffic. This relatively high resolution may increase concentration accuracy but also has implications for usability, both discussed below.
- Accuracy: An accurate estimate of what people breathe can be important when making the case to regulators that certain policies should or should not be implemented, particularly in reference to regulatory standards or health impact calculations. In this case, Nguyen and Marshall chose to use CAMx with model inputs from the Multiple Air Toxics Emissions Study III (MATES III) because of their past use within the study domain.[75] CAMx was previously validated for use in California by the California Air Resources Board, a department within California's Environmental Protection Agency. Additionally, MATES III had been used in Southern California with an average predictive accuracy of 17% for fine elemental carbon particulate matter, which is well within the guidelines set by the US Environmental Protection Agency of 30%.
- Usability: To improve efficiency, they combined using the CTM for representative grid cells with KI to estimate others. The CTM and KI combination produces concentration estimates that are accurate enough to assess relative changes in concentration and exposure. The main advantage of using a hybrid method comes from the increase in usability by only modeling select cells and using KI to create an exposure surface. While this hybrid approach does decrease the accuracy of concentration estimates and therefore the accuracy of exposure estimates, the trade-off is greatly increased usability and interpretability.

Summary of EJ Findings. This case study explores scenarios where low-emission zones and truck rerouting are implemented in areas of Southern California. Four metrics are used to assess each scenario's impacts on $PM_{2.5}$: total inhalation intake by the population to measure impact, mass of pollutant inhaled per mass emitted to measure efficiency, dissimilarity index to measure inequality, and difference in average exposure for minority and white non-Hispanics to measure injustice. Before assessing scenarios, the authors note that the intake fraction of $PM_{2.5}$ from diesel engines is 18 ppm, which means 18 g is inhaled per million grams emitted. Additionally, the dissimilarity index value is 0.20, meaning exposure equality could be achieved by redistributing 20% of exposures. Finally, mean exposure to diesel-related $PM_{2.5}$ is 2.25 μg m^{-3} for minorities, while it is 1.63 μg m^{-3} for white non-Hispanics. From the authors' scenario simulations, they identified areas where implementation of low-emission zones would improve all four metrics. While implementing truck rerouting results in lower reductions in inequality and injustice, the alternative routes still improve inequality and injustice metrics. A major finding of this critical review is that emission reductions in minority and low-income neighborhoods may not be the best means of achieving improvements in injustice and inequality due to how the pollutants travel after they are emitted.

Discussion of Potential Trade-Offs. Questions of targeted intervention demonstrate the need for high interpretability and high efficiency, as they require the ability to separate the effects of different inputs and may require analysis of many scenarios. Additionally, it is necessary to use the appropriate spatiotemporal resolution to capture the effects of any variation in inputs. Interpretability and efficiency may be difficult to achieve simultaneously, depending on the scale of the study. One potential mitigation technique is reducing the expectation of accuracy, particularly when there is confidence in an approach's ability to capture the magnitude of differences between intervention scenarios, even if the uncertainty in absolute levels is higher. In the example discussed above, hybridization of a CTM with a less accurate but more efficient method may have been a way to balance between these criteria. The above example is focused on prospective planning and policy design; however, some (technology, policy, behavioral) intervention-oriented questions may be focused on posthoc evaluation. In these cases, monitor-based studies may be critical. However, attributing observed changes to specific interventions could be facilitated by adopting the high interpretability and high efficiency methods described above.

■ FUTURE RESEARCH DIRECTIONS

The body of EJ research is growing quickly, expanding in geographic coverage, scope of topics, and range of methods. Besides the explosion of interest in different geographic areas, the field is continually evolving in the context of other air pollution research advances, such as the proliferation of data, evidence regarding additional impacts on health and development, the growth of statistical methods, increased societal concerns about inequality, and new policy directions.

With the growing use of low-cost and mobile monitors, researchers have access to an extremely large repository of data.[153,185] These emerging monitoring methods expand opportunities for community engagement with EJ studies. Historically, the lack of data has been used as an excuse for inaction. This argument is increasingly becoming untenable. However, researchers must take care to avoid extractive relationships with communities.[186,187] EJ studies may additionally choose to use methods mandated by regulatory processes, such as dispersion modeling, to comply with regulatory standards.[67,173,180] Hyperlocal data from newly

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accessible methods also hold great potential for better visualization of pollution distributions, offering an important tool for communities, activists, and policy makers.

The uptake of advanced statistical methods (i.e., machine learning, computer vision) in the air pollution field has accelerated in recent years with applications to EJ beginning to catch up. The increased availability of data means these methods are becoming more necessary. Novel applications of using photographs to estimate air quality and sociodemographic characteristics are ripe for exploitation within the EJ field.[188] In some cases, interpretability may limit the extent to which these methods are used, but they are sure to adapt and grow with new research questions.

New policy directions in the EJ field will inform weighting of considerations in the method selection process. Activists have long urged the consideration of cumulative effects in the context of environmental justice. Within the science and engineering community, there is increasing emphasis on the importance of both cumulative health effects from multiple pollutants and from living with air pollution as well as other stressors.[154,189−191] EJ research has always had a strong interdisciplinary focus, but there is a growing appreciation for the integration of both qualitative and quantitative data to explore communities' lived experiences and holistically assess a community's complete environment.[192] With this relatively new appreciation for holistic methods within science and engineering comes the need to increase dialogue with a broader audience.[193] Researchers and communities must work together to develop effective means to convince policy makers and decision makers of the vital importance of addressing EJ concerns. In the future, more science based EJ research will be available, potentially enabling the general public, communities, and activists to participate meaningfully in the policy process. There has been steadily increasing attention to EJ from policy makers, for instance, in the US and Canada.[194,195] Given the pervasiveness of air pollution, identifying effective, efficient, and equitable solutions should be a public policy priority in many nations.[196] The involvement of diverse actors including communities, researchers, and policy makers will be critical in the future to ensure a representative process.

Finally, identifying and supporting EJ communities goes beyond elements of this framework and study methods. It entails more than estimating pollution concentrations. The overarching goal of EJ research within air pollution is to identify air pollution disparities based on sociodemographic characteristics, to describe the contexts in which they occur, and to determine mitigation strategies. However, the path from estimating pollutant concentrations to quantification of distributive injustice is not straightforward, requiring a significant amount of work, thought, and experimentation.[149] What equity means within the air pollution and EJ space and how to model it are questions that are not definitively settled and which may require a place and context-based approach.[197] Achieving EJ goals may benefit from estimation of air pollution concentrations and assessment of disparities, but these estimates are not in and of themselves sufficient. A societal imperative, articulated by the UN Sustainable Development Goals, is to "leave no one behind," including healthy lives for all.[198] For researchers, this highlights the importance of addressing the most highly polluted regions and communities, for whom the gap between today's air quality and the goal of clean air is the greatest. To ensure that EJ communities have been properly identified, researchers must work collaboratively with communities that are disproportionately burdened by air pollution.[49] Many methods for studying air pollution do not adequately account for other aspects that may characterize EJ communities and engagement can facilitate their consideration. For example, environmental hazards can tie in with the perception of neighborhoods, lack of jobs within the community, and lack of access to food for many EJ communities.[49,199,200] All of these issues have the potential to compound with lack of access to healthcare and worsen the health effects of air pollution for residents. Accurately identifying EJ communities can be vital to helping disadvantaged communities access necessary resources and attention.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c01739.

Additional case study applications, examples of research questions, and tabulated details on selected EJ and air pollution studies (PDF)

■ AUTHOR INFORMATION

Corresponding Author

Amanda Giang − *Department of Mechanical Engineering, University of British Columbia, Vancouver V6T 1Z4, Canada; Institute for Resources, Environment and Sustainability, University of British Columbia, Vancouver V6T 1Z4, Canada;* orcid.org/0000-0002-0146-7038; Email: amanda.giang@ubc.ca

Authors

Rivkah Gardner-Frolick − *Department of Mechanical Engineering, University of British Columbia, Vancouver V6T 1Z4, Canada*

David Boyd − *Institute for Resources, Environment and Sustainability, University of British Columbia, Vancouver V6T 1Z4, Canada*

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.1c01739

Notes

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■ ABBREVIATIONS

EJ, environmental justice; UHC, unit hazard coincidence; HAP, hazardous air pollutant; TRI, Toxic Release Inventory; KI, Kriging interpolation; LUR, land use regression; ML, machine learning; CTM, chemical transport model; RCM, reduced complexity model; TRAP, traffic-related air pollution

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