Health and Inequality Metrics for Urban-scale Air Quality Management

by

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DEDICATION

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ABSTRACT

Despite the successes of the Clean Air Act in the United States, ambient air pollution continues to be an important public health and environmental justice challenge. These challenges are especially evident at the local scale, where gradients in exposures, risks, and vulnerability may be sharp and align spatially, leading to disproportionate impacts. The goals of this dissertation are to use quantitative health impact assessment (HIA) techniques with inequality metrics to estimate the health burden attributable to ambient air pollution at a local scale, to better understand how health burdens are distributed across populations, and to assess air quality management (AQM) strategies for reducing this burden. The work is based in Detroit, MI and several adjacent cities, an urban area with a legacy of air quality challenges. The first aim examines health impact metrics used in the literature and makes recommendations about which metrics are most appropriate for AQM studies. Multiple metrics are recommended to meet the diverse needs of AQM stakeholders, specifically the number of attributable cases of mortality and morbidity, disability-adjusted life years, and monetized impacts. The second aim quantifies the health burden and inequality due to ambient air pollutants in Detroit, and apportions this burden to source types, e.g., regional, point, and mobile sources. The HIA results show fine particulate matter ($PM_{2.5}$) and ozone have the highest total health burdens on the population and that exposures to $PM_{2.5}$, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2)

from point and mobile sources have disproportionate impacts on vulnerable populations. The third aim examines the potential health benefits of two strategies to reduce air pollutant exposures: decreasing SO_2 emissions at nearby industrial facilities and installing particulate matter filters in homes and schools in the area. The first strategy analysis, which compares alternative approaches to reducing emissions of SO_2 at major point sources in the study area, demonstrates that using health and inequality metrics when comparing alternatives can identify point source controls strategies that better meet AQM and health goals. This study also suggests the control strategy proposed by the Michigan Department of Environmental Quality to attain compliance with the SO_2 standard will have only modest health benefits for residents of Detroit and will do little to alleviate disparities in SO_2 health burdens. The second strategy analysis, which estimates the benefits of filters with different efficiencies, indicates that the widespread use of filters, especially in schools, can be a cost-effective strategy for reducing asthma burdens for school-aged children in the area. Overall, the results of this dissertation indicate air pollution continues to be public health and environmental justice challenge for Detroit, MI, and that quantitative HIA metrics combined with key inequality metrics can support AQM decision-making to select alternatives that improve public health and reduce health disparities.

Chapter 1

INTRODUCTION

Background

Ambient air pollutant exposures are an important environmental risk factor for morbidity and mortality with a large impact on public health. The associations between air pollutant exposures and many adverse health effects are well documented. Studies in the US and elsewhere have demonstrated the link between premature mortality and exposures to particulate matter (PM) (Hoek et al. 2013; Krewski et al. 2009) and ozone (O_3) (Bell et al. 2005; Jerrett et al. 2009). PM likely contributes to the development of cardiovascular disease and can trigger adverse cardiovascular events, e.g., heart attacks, primarily among susceptible individuals (Brook et al. 2010). Exposures to O_3, nitrogen dioxide (NO_2), and PM have been associated with exacerbations of respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and respiratory infections (Kelly and Fussell 2011). There is also emerging evidence that air pollutant exposures are associated with non-cardiopulmonary outcomes, e.g., autism spectrum disorder (Volk et al. 2013), neurological diseases (Loane et al. 2013), and adverse birth outcomes (Sapkota et al. 2012), although the evidence for these associations is weaker and causality has not yet been established.

The burden of disease attributable to ambient air pollutant exposures in the United States and globally is substantial. In the US, exposures to PM with an aerodynamic diameter less than 2.5 µm ($PM_{2.5}$) and O_3 are responsible for 6% of annual premature mortalities nationally, ranging from under about 4% in the upper Midwest and Southwest portions of the country to almost 10% in the industrial Midwest and southern California (Fann et al. 2012). Morbidities due to these pollutants are numerous and include 150,000 hospitalizations for respiratory and cardiovascular diseases, 2.5 million days with asthma symptoms, and 11 million missed school days each year (Fann et al. 2012). Globally, ambient $PM_{2.5}$ and O_3 exposures are estimated to cause 4.2 million and 0.25 million deaths, respectively, each year, resulting in a total of 107 million disability-adjusted life years (DALYs) lost (Forouzanfar et al. 2016). Much of this health burden is avoidable since most exposures can be mitigated through appropriate air quality management approaches.

Ambient air pollution continues to also be an important environmental justice challenge in the United States, in particular within urban areas. Concentrations of ambient air pollutants may vary widely across a city, and higher exposure levels often coincide with individual- and population-level factors that increase susceptibility or vulnerability to air pollution. Susceptibility refers to intrinsic factors that tend to intensify the response due to an exposure, such as advanced age or the presence of chronic disease; vulnerability refers to extrinsic factors that can increase exposures or reduce the ability to respond to exposures, such as the location of a residence relative to a pollutant source or lower socioeconomic status (SES) (O'Neill et al.

2012; Sacks et al. 2011). The combination of these factors at the individual and community level can lead to sensitive subpopulations with characteristics that increase the risk of air pollution-related health effects (Sacks et al. 2011). Often, these sensitive subpopulations are racial or ethnic minority groups and low-income communities. As an example, traffic is a significant source of air pollution in urban areas that displays high spatial variability (Health Effects Institute 2010). Minority and low-income populations in the United States are more likely to live near major roads (Boehmer et al. 2013), and may experience inequitable health outcomes as a result of higher pollutant exposures (Stuart et al. 2009). In many urban areas (including Detroit, Michigan), minority and low-income populations are exposed to multiple environmental and social stressors, e.g., proximity to hazardous land uses or low educational attainment, that increase their vulnerability or susceptibility to ambient air pollution (Sadd et al. 2011; Schulz et al. 2016). Thus, the combination of environmental exposures, social stressors, biological susceptibility, and social vulnerability that results in cumulative adverse impacts for some subpopulations in the urban environment should be considered when establishing air quality management policies (Morello-Frosch et al. 2011).

Air quality management in the United States

Current air quality regulation in the US is based on the framework established in the Clean Air Act (CAA; 1970) and the subsequent CAA Amendments of 1990. The CAA Amendments establish programs designed to establish health protective standards for ambient concentrations of pollutants, monitor air quality using reproducible and quality-assured approaches, control emissions though technological controls on stationary (i.e., point) and mobile sources, and ensure compliance with these health protective standards through permitting programs (42 USC §7401-7671).

Under the authority of the Clean Air Act, the US Environmental Protection Agency (US EPA) Administrator establishes National Ambient Air Quality Standards (NAAQS) for individual pollutants. The NAAQS are established based on the strength of the existing toxicological and epidemiological data and are intended to be protective of sensitive populations (NRC 2004). Relevant data are summarized in the Integrated Science Assessments (ISA; e.g., US EPA 2008b, 2009, 2013, 2016) and used to identify a value for the standard, including the concentration and averaging time, e.g., daily mean or 8-hour maximum concentration. US EPA staff also develop a Risk and Exposure Assessment and a Policy Assessment to inform the agency Administrator's decision (Sacks et al. 2015).

NAAQS compliance determinations are based on ambient concentrations over relatively large geographical areas, typically using measured concentrations at air quality monitors in an urban-scale airshed. National monitoring ("trend") sites are chosen to obtain broadly representative concentration measurements, and state and local air monitoring stations are positioned to provide additional spatial coverage (MDEQ 2015b; US EPA 2008a). Monitors are sometimes strategically placed in areas where concentrations are expected to be high, e.g., near-roadway monitors for NO_2 (MDEQ 2015b). In some cases, compliance can be determined using air quality models that simulate the processes of emissions and dispersion.

For areas that do not meet the NAAQS, states are mandated by the CAAA to develop state implementation plans (SIPs) to achieve compliance with the national standards and any other state-level requirements for air quality (Cote et al. 2008). SIPs are developed using emissions inventories and air quality models to determine if and where emissions reductions are required (NRC 2004). The goal of a SIP is to reduce emissions enough to ensure ambient concentrations are below the standard.

Though the CAA Amendments have been successful in reducing emissions and ambient concentrations of criteria pollutants since their implementation, current AQM programs may not be fully protective of public health for several reasons. First, the language of the CAA Amendments indicates that NAAQS should be protective of public health, even for sensitive subpopulations. However, population-level thresholds below which exposures are thought to not cause health effects have not yet been established (Bell et al. 2006; Cesaroni et al. 2013; Daniels et al. 2004; Schwartz et al. 2002). In the absence of known thresholds, the NAAQS are ultimately policy decisions that result in residual risks of adverse health effects (Bachmann 2007; McClellan 2012), e.g., recent studies having identified mortality risks for $PM_{2.5}$ and O_3 exposures below the current NAAQS (Di et al. 2017; Schwartz et al. 2017; Shi et al. 2016). Further reducing air pollutant concentrations below NAAQS levels can lead to additional public health benefits (Pope et al. 2015). Second, monitoring networks used in compliance determinations are often sparse and fail to capture intra-urban variation of pollutant levels (Hubbell 2012; Levy and Hanna 2011; Matte et al. 2013). The small-scale variation in concentration gradients at the urban scale results in exposures that are heterogeneous, e.g., higher exposures can occur near pollutant sources such as near highly trafficked roads (Isakov et al. 2009); some exposures could exceed the NAAQS even when an area is designated as in attainment of the standard. Third, cumulative impacts are still not well incorporated into the regulatory process (Alves et al. 2012). As discussed earlier, populations experiencing multiple social and environmental stressors, including other air pollutants, are likely to respond more strongly to the same exposure concentration than populations with lower cumulative impacts. Other factors that may result in lower public health protections include the lengthy process of first designating an area as non-attainment and then developing the SIP, during which populations are exposed to unacceptable levels of pollutants, and the focus on single pollutant exposures rather than mixtures of air pollutants (NRC 2004).

Addressing the public health challenge of ambient air pollution at the urban scale

Addressing the public health challenge of ambient air pollution at the urban scale can be done at several levels, e.g., national, regional, or local, and using different approaches. The CAA provides a regulatory framework focused primarily on limiting emissions of air pollutants, e.g., through permitting programs, enforcement and compliance actions, and the SIP process. In addition to federal regulations, states and municipalities can also pass their own clean air legislation to limit emissions, e.g., Detroit's anti-idling ordinance to reduce emissions of diesel particulate matter (DPM). Outside the regulatory framework, emissions and exposure reduction strategies can be useful. Examples of local-scale strategies that can be implemented by governmental and non-governmental actors include encouraging sensitive individuals to remain indoors on days with poor air quality (Wen et al. 2008), limiting school bus diesel emissions near schools (Ryan et al. 2013), utilizing buffers near roads to disperse traffic pollutants (Baldauf et al. 2008; Hagler et al. 2012), and increasing the use of filtration in sensitive environments such as schools and homes located near major roads (Batterman et al. 2012; McCarthy et al. 2013; Polidori et al. 2013).

This dissertation focuses on one regulatory approach, i.e., the use of control technologies to reduce emissions of pollutants at stationary (point) sources, and one exposure reduction approach, i.e., the use of filters to reduce indoor exposures to outdoor pollutants. These strategies are discussed next.

The SIP process mandated by the CAA Amendments favors the use of technology-based source controls for existing major point sources of criteria pollutants (NRC 2004). Point source emission controls have long been used to remove pollutants from waste effluents before they can be emitted into the air, e.g., using electrostatic precipitators and scrubbers to remove particulate and gaseous pollutants (Crawford 1976; Stern 1968). Using a technology-based approach was originally thought to bring about broad and diffuse environmental and health benefits (Ingram 1978). However, more recent analyses indicate the health benefits of point source controls vary based on the location of a facility, its specific source characteristics e.g., stack heights, local meteorology, proximity of sources to populations, and population susceptibility or vulnerability (Fann et al. 2009); not all approaches to controlling point source emissions will result in optimal reductions in health risks or inequality (Levy et al. 2009). Thus, it is important to consider the unique distribution of sources and populations in an urban area when designing control strategies to achieve compliance with the NAAQS to simultaneously optimize health benefits and minimize inequities.

When emissions reductions are impractical or infeasible, e.g., when an area is in attainment of the NAAQS and there is no regulatory pressure to reduce emissions, reducing exposures becomes an important strategy for lowering health burdens due to ambient air pollution. Exposure reduction strategies such as filters are an attractive option at the local scale because there are often multiple sources of pollutants which are not easily controlled, e.g., local point and mobile sources and secondary formation from regional pollutant emissions. As is the case with point source controls, the potential benefits from emissions reductions strategies depends on several local factors. As an example, the effectiveness of filters to reduce exposures to particulate matter depends on building- and location-specific parameters, e.g., how long filters are used, outdoor conditions (e.g., wind direction, temperature), tightness of the building envelope, and particle composition and size (Breen et al. 2014; Hodas et al. 2012; Isaacs et al. 2013; Stephens, 2015), as well as individual-level characteristics, e.g., underlying susceptibility and time-activity patterns. Because these parameters can vary widely between cities, place-based assessments are needed to determine if filters (or other exposure reduction strategies) are likely to have a substantial health benefit.

As discussed above, effectively implementing strategies to reduce the health burden due to ambient air pollution at the urban scale requires detailed information on where health impacts occur and how effective various air quality management strategies might be. Therefore, a framework for assessing benefits of emissions and exposure reductions that accounts for these location-specific factors is needed. Such a framework needs to be flexible enough to account for important place-based factors that affect air pollutant exposures and health burdens (Hubbell 2012) and amenable to the use of various health impact and health equity metrics to aid in decision making.

Health impact assessment

Health impact assessment (HIA) provides a framework for evaluating potential AQM strategies. HIA aims to identify the health impacts of a project or policy and recommend steps to mitigate them (Collins and Koplan 2009). The framework for HIA is similar to that used in environmental impact assessment. Full HIAs include six key steps: screening for decision alternatives; scoping the assessment by selecting which determinants and health outcomes to include; assessing existing conditions and predicting the health impacts of the project or policy; developing recommendations for addressing the health impacts; reporting findings to stakeholders and decision makers; and, evaluating the HIA process and the outcomes of the assessment (Bhatia et al. 2014). Recognizing that decisions in non-health sectors, e.g., transportation or urban planning, affect public health, HIAs are conducted to ensure that potential health impacts are considered in the broader urban policy context (Bhatia and Corburn 2011; Collins and Koplan 2009; Dannenberg and Wernham 2013; Gase et al. 2013; NRC 2011).

HIA uses a combination of tools, procedures, and methods to predict intended and unintended health impacts of proposed projects, policies and plans across public sectors (Bhatia et al. 2014;

Dannenberg and Wernham 2013). HIA methods have been used to evaluate the disease burden due to pollution (Fann et al. 2012), to predict the incremental impact of alternative policies and scenarios, e.g., different levels of an ambient standards (Yang and Kao 2013), and to apportion health impacts by source industry (Fann et al. 2013). At regional (sub-national), urban, and project scales, HIAs can be conducted in a policy context, but more commonly are used to gauge potential impacts and benefits of specific actions, e.g., transportation planning (James et al. 2014; Maizlish et al. 2013). Due to limitations in scope and available data, most HIAs conducted in the US have been qualitative rather than quantitative (Rhodus et al. 2013). While qualitative assessments can convey the direction and magnitude of impacts, quantitative methods offer more explicit information regarding impacts of potential interventions or the status of abatement policies (Bhatia and Seto 2011).

Several tools have been developed to facilitate HIAs. Qualitative assessments can benefit from environmental justice screening tools such as EJSCREEN (US EPA 2015b). These tools are useful for describing the baseline characteristics of a study area in an HIA and identifying potentially overburdened communities, but they do not quantify health impacts attributable to specific exposures, e.g., ambient air pollution. In contrast, quantitative tools for HIAs, including US EPA's Benefits Mapping and Assessment Program (BenMAP), use epidemiological data describing the associations between environmental determinants of health and the risk of adverse health outcomes to calculate the fraction of mortality or morbidity attributable to exposures (Anenberg et al. 2015; US EPA 2015a). BenMAP and other quantitative tools can be customized to fit various HIA scales, e.g., national (Berman et al. 2012; Voorhees et al. 2014) or urban (James et al. 2014), using area-specific data, but are usually limited to health impact metrics (e.g., attributable cases of morbidity and mortality) and do not include metrics for inequality or environmental justice. None of the existing tools is capable of comprehensively assessing the AQM strategies considered in this research with respect to health and equity concerns. Therefore, a new analysis framework that combines health and inequality metrics is needed.

Objectives and Specific Aims

The objectives of this dissertation are to use quantitative health impact assessment (HIA) techniques with inequality metrics to estimate the health burden attributable to ambient air pollution at a local scale, to better understand how health burdens are distributed across populations, and to assess air quality management (AQM) strategies for reducing this burden. The research uses quantitative HIA methods with environmental justice metrics to evaluate AQM strategies and strategies to reduce exposures with the intention of developing an evidence base for decision makers about how to effectively and equitably reduce ambient air pollutant exposures and their impacts in an urban environment.

The specific aims of this dissertation are:

<u>Specific Aim 1</u>*: Identify quantitative health impact metrics that are appropriate for studies meant to inform air quality management decisions.* Previous work has established methods for estimating attributable health impacts, which can be expressed using several metrics, but

guidance on best practices for the development and use of HIA metrics for environmental heath decision making is lacking.

<u>Specific Aim 2</u>: *Assess the public health burden and health disparities attributable to current levels of ambient air pollutants in the study region using a quantitative impact assessment framework that considers population vulnerabilities, spatial resolution, and uncertainty, and that uses a comprehensive set of health and inequality metrics.* Quantifying the public health burden and health disparities due to pollutant exposures in the study area is important for identifying which air pollutants or air pollutant sources should be the focus of local-scale AQM and exposure reduction efforts.

<u>Specific Aim 3</u>: *Evaluate selected strategies for reducing air pollutant concentrations, exposures and health impacts in the study region using quantitative HIA methods*. This aim is intended to demonstrate how HIA methods can be used to generate policy-relevant information in regulatory and non-regulatory contexts. Two different approaches to reduce health burdens are considered: point source controls to reduce emissions and filters to reduce exposures indoors.

Research context

A study area that includes Detroit, Michigan and several adjacent “downriver” cities (Hamtramck, Highland Park, Dearborn, Melvindale, Allen Park, Lincoln Park, Ecorse, and River Rouge) offers an ideal setting for using quantitative HIA methods to evaluate intra-urban scale approaches to burden of disease studies and HIAs of alternative air quality management strategies. Figure 1.1 shows where these cities are located in southeast Michigan. Air pollution continues to be an important environmental health concern for residents of southeast Michigan and Detroit in particular (Lougheed 2014). Currently, Michigan is in attainment of the particulate matter ($PM_{2.5}$ and PM_{10}), NO_2, lead[1], and O_3 NAAQS (MDEQ 2015a). A portion of the I-75 Corridor in Wayne County, which includes the study area and is represented by the monitor at Southwest High School, does not meet the 1-hour SO_2 standard (MDEQ 2016b), and recently the Michigan Department of Environmental Quality (MDEQ) submitted to US EPA a recommendation that the entire seven county region of southeast Michigan be designated as non-attainment with the 2015 O_3 standard (MDEQ 2016a). Although most of the NAAQS are now attained, residents of the study area experience adverse health effects due to ambient air pollutant exposures. For example, 7.3% of premature mortalities in Wayne County have been attributed to $PM_{2.5}$ and O_3 exposures (Fann et al. 2015). The area's history as an industrial center means there are many point sources in the area, including steel mills, coal fired power plants and oil refineries, as well as a legacy of much higher pollutant concentrations. Transportation is also an important source of air pollution in the region. Southeast Michigan has over 23,000 miles of major roads, 4,000 miles of truck routes, five commercial marine ports and seven rail and truck terminals (SEMCOG 2013).

[1] There is a small section of Ionia county that is currently designated as non-attainment for the lead NAAQS (MDEQ 2015a). US EPA recently approved the state's request to re-designate the area as in attainment effective July 31, 2017 (US EPA 2017).

Residents of the study area experience health disparities that can be addressed in part by reducing exposures to ambient air pollutants. The population of Detroit, the largest city in the study area, is primarily minority (83% Black and 7% Latino) and 39% live below the poverty line (US Census Bureau 2015). Demographics across the study area are similar, e.g., 66% identify as Black or African American, 7.5% identify as Hispanic or Latino, and 37% live below the poverty line (Table 1.1; US Census Bureau, 2014). Demographics and poverty status vary between cities included in the study area, which was selected based on the potential for high exposures to air pollutants. The percentage of residents who are persons of color ranges from 12.5% in Allen Park to 94.2% in Highland Park, and the percentage of residents who are in poverty ranges from 7.2% in Allen Park to 48.5% in Hamtramck (Table 1.1). Asthma disparities between the study area and the rest of Wayne County or Michigan as a whole are significant, e.g., the population-weighted asthma hospitalization rate for the study area (41.3 cases per 10,000 per year) exceeds that of Wayne County (28.9 per 10,000) and the state of Michigan as a whole (14.8 per 10,000; Table 1.1) (MDHHS, 2017). Residents also experience a high prevalence of obesity, diabetes, and smoking compared to the state as a whole (MDHHS 2015), suggesting increased vulnerability to adverse health impacts of air pollutants. Recent studies have documented the health effects of cumulative social and environmental exposures on residents of Detroit in particular, e.g., higher cortisol levels among older African Americans living in neighborhoods with high disadvantage scores (Zilioli et al. 2017) and stronger relationships between $PM_{2.5}$ exposures and blood pressure for residents in southwest Detroit reporting higher levels of stress (Hicken et al. 2014), suggesting Detroit residents and residents of similarly impacted cities would benefit from policies designed to improve environmental conditions.

Portions of the work in this dissertation were conducted to support an ongoing community based participatory research (CBPR) study. Community Action to Promote Healthy Environments (CAPHE) is a CBPR partnership working to develop and implement strategies to reduce the adverse health effects of air pollution in Detroit. Partners include local universities, community based organizations, environmental groups, and state and local agencies. The work of the CAPHE Core Team and the Steering Committee helped inform several of the analyses presented here, including the identification of preferred strategies for AQM in the area (Specific Aim 3). This research is intended to inform a variety of stakeholders interested in improving urban health. While the research focuses on Detroit, Michigan and several adjacent cities, methods and potentially many key results would apply to other urban areas.

Outline of the dissertation

This dissertation is organized into six chapters. Chapter 1 provided an overview of the health effects of ambient air pollutants, described the current framework for AQM in the United States and the limitations of this framework with respect to public health, introduced the HIA framework used in the dissertation, identified the specific aims for the work, and described the study area.

Chapter 2 presents and evaluates quantitative metrics used in HIAs and similar analyses that are relevant to air quality management at urban and potentially regional scales (Specific Aim 1). The analysis fills an important gap in the literature by identifying which metrics are most important for the local-scale analyses featured in this dissertation. The metrics are evaluated using explicit criteria, and demonstrated using a case study that focuses on $PM_{2.5}$. The chapter concludes with recommendations for metrics that can best inform decision-makers. The findings from Chapter 2 inform the remaining data chapters in the dissertation.

Chapter 3 examines the health burden and health disparities attributable to air pollutant exposures in Detroit, Michigan and adjacent downriver cities (Specific Aim 2). These cities, shown in Figure 1.1, have the potential for high exposures and high health impacts due to a number of important factors, including the proximity of point sources and heavily trafficked roads, higher baseline health rates, and potentially higher degrees of vulnerability or susceptibility. Few burden of disease studies at the urban scale have been conducted, and this is the first burden of disease assessment for Detroit, MI. In this chapter, the quantitative HIA framework developed in Chapter 2 is expanded to include inequality metrics relevant to environmental justice studies. The analysis uses a comprehensive HIA dataset for the study area that contains spatially- and temporally-resolved data on demographics, health outcomes, ambient air pollutant concentrations and source-receptor relationships, concentration-response functions and the social and environmental determinants of health. Impacts due to five pollutants ($PM_{2.5}$, NO_2, SO_2, O_3, and diesel exhaust particulate matter) are evaluated in a spatially explicit analysis. Results are presented for total exposures and exposures to specific source categories, e.g., point or mobile sources. Sensitivity of the results to spatial resolution and study boundaries is examined, and recommendations for intra-urban studies are discussed.

The results of Chapter 3 are used to identify which pollutants or pollutant sources are included in the analyses to address Specific Aim 3.

Chapters 4 and 5 address Specific Aim 3 by evaluating air quality management strategies for the study area. Chapter 4 investigates emission control strategies aimed at reducing the burden of disease and health burden inequalities from point sources of SO_2, which are identified in Chapter 3 as having a disproportionate impact on susceptible or vulnerable populations in the area. The analysis is timely because a portion of the study area is currently out of attainment with the SO_2 NAAQS, and in response to this designation MDEQ was required to develop a SIP to address SO_2 emissions. Alternative strategies to reduce emissions are formulated and evaluated in terms of ambient concentrations, total health benefits, and the distribution of health impacts across an urban population. The analysis quantifies the potential trade-offs between emission reductions, health impacts, and inequality, and demonstrates how health burden and inequality metrics might be used at an urban scale and in a regulatory context.

Chapter 5 evaluates the health benefits among school-aged children in the study area of using filters in schools and homes to reduce indoor exposures to ambient $PM_{2.5}$. $PM_{2.5}$ is identified as a major contributor to the air pollution-related health burden experienced by study area residents, and emissions point and mobile sources in the area disproportionately impact vulnerable populations (Chapter 3). The public health benefits of filters among children has received little attention in the literature, and this analysis addresses this gap by focusing on the two microenvironments (e.g., schools and homes) in which children spend most of their time.

Chapter 6 summarizes the main findings; discusses the tradeoffs of selected air quality management (AQM) strategies for Detroit; examines how quantitative HIA methods can be used to guide local decision making and how including HIA methods in the environmental decision process can potentially lead state and national environmental policy towards more equitable goals; addresses barriers and challenges for local scale assessments, including communicating results to decision makers; and, suggests directions for future studies.

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Table 1.1 Selected demographic and economic characteristics, and crude rates of all-cause mortality and asthma hospitalization for the study area, Wayne County, Michigan, and individual cities within the study area. Some baseline health rates are not available at the city level and are omitted.

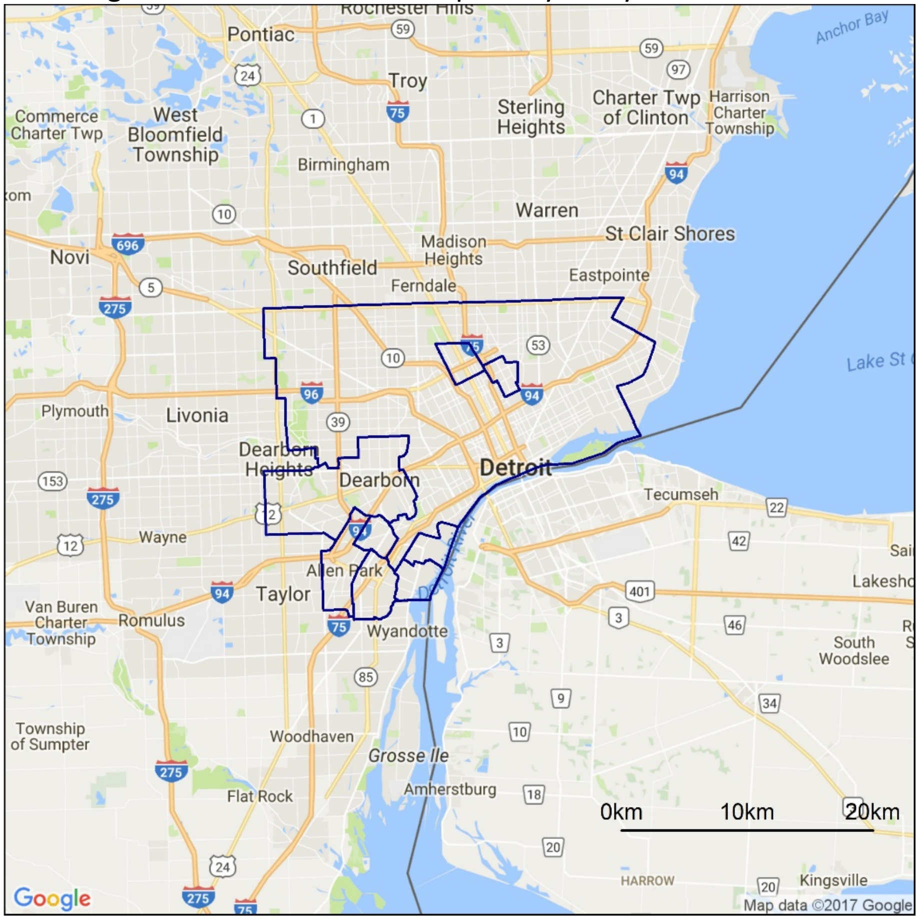
Variable	Study area	Wayne County	Michigan	Allen Park	Dearborn	Detroit	Ecorse	Hamtramck	Highland Park	Lincoln Park	Melvindale	River Rouge
Demographics and Poverty												
% Black or African American	65.9	40.9	15.3	3.2	4.1	82.5	44.5	14.5	92.7	7.2	16.1	62.3
% Hispanic or Latino	7.3	5.5	4.6	8.6	3.5	7.3	14.5	1.1	0.3	16.6	12.6	13.2
% Non-Hispanic white	24.4	49.8	76.1	87.5	87.3	8.7	38.4	56.0	5.8	75.3	67.7	33.0
% Persons in Poverty	36.8	24.8	23.7	7.2	28.6	39.8	27.1	48.5	47.6	19.5	28.6	39.4
Baseline Incidence Rates[1]												
Crude mortality[1]	1024.8	985.4	902.5	1153.5	822.5	1047.7		666.6	1456.2	1056.0		
Asthma hospitalization[2]	41.3	28.9	14.8			47.9						

[1] Population-weighted incidence rates for the study area are estimated from data at the ZIP code level. Incidence rates are not restricted by age. Mortality and hospitalization rates for Wayne County, Michigan, and the individual cities are taken from MDHHS (2017)

[2] Crude mortality rate calculated per 100,000

[3] Asthma hospitalization rate calculated per 10,000

Figure 1.1 Map showing the cities included in the primary study area.



Chapter 2

HEALTH IMPACT METRICS FOR AIR POLLUTION MANAGEMENT STRATEGIES

Abstract

Health impact assessments (HIAs) inform policy and decision making by providing information regarding future health concerns, and quantitative HIAs now are being used for local and urban-scale projects. HIA results can be expressed using a variety of metrics that differ in meaningful ways, and guidance is lacking with respect to best practices for the development and use of HIA metrics. This chapter reviews HIA metrics pertaining to air quality management and presents evaluative criteria for their selection and use. These are illustrated in a case study where $PM_{2.5}$ concentrations are lowered from 10 to 8 μg/m^3 in an urban area of 1.8 million people. Health impact functions are used to estimate the number of premature deaths, unscheduled hospitalizations and other morbidity outcomes. The most common metric in recent quantitative HIAs has been the number of cases of adverse outcomes avoided. Other metrics include time-based measures, e.g., disability-adjusted life years (DALYs), monetized impacts, functional-unit based measures, e.g., benefits per ton of emissions reduced, and other economic indicators, e.g., cost-benefit ratios. These metrics are evaluated by considering their comprehensiveness, the spatial and temporal resolution of the analysis, how equity considerations are facilitated, and the analysis and presentation of uncertainty. In the case

study, the greatest number of avoided cases occurs for low severity morbidity outcomes, e.g., asthma exacerbations (n=28,000) and minor-restricted activity days (n=37,000); while DALYs and monetized impacts are driven by the severity, duration, and value assigned to a relatively low number of premature deaths (n=190 to 230 per year). The selection of appropriate metrics depends on the problem context and boundaries, the severity of impacts, and community values regarding health. The number of avoided cases provides an estimate of the number of people affected, and monetized impacts facilitate additional economic analyses useful to policy analysis. DALYs are commonly used as an aggregate measure of health impacts and can be used to compare impacts across studies. Benefits per ton metrics may be appropriate when changes in emissions rates can be estimated. To address community concerns and HIA objectives, a combination of metrics is suggested.

Introduction

Air quality management requires the consideration of a complex array of technical, economic, legal and political factors. In the U.S., statutory obligations are placed on state and local governments to attain ambient concentrations and meet other standards set by the US Environmental Protection Agency (US EPA). Historically, compliance with standards has been achieved by emissions reduction strategies that addressed a single pollutant at a time, and targeted local and culpable sources for emissions reductions, at the same time incorporating effects of the broader emission reductions accomplished by national emissions standards. As air quality standards continue to be strengthened and easily implemented controls become rarer, decision makers must consider a wider range of policy measures. Since interventions aimed at reducing ambient pollution levels can affect the health of those living and working in the affected area (Henschel et al. 2012), it is becoming increasingly important to assess the nature and magnitude of potential health impacts, thus avoiding both unintended health consequences and missed opportunities to improve public health (NRC, 2011).

Health impact assessments (HIAs) use a variety of techniques to evaluate and compare potential health impacts of proposed projects, policies and plans with the key objectives of understanding the direction, magnitude, severity, and distribution of impacts (Bhatia et al. 2014). HIAs and similar analyses have been conducted at multiple scales and for different purposes. At the national or global scale, accountability research, burden of disease, and other studies are used to evaluate the disease burden due to pollution (Fann et al. 2012b; Lim et al. 2012), the incremental impact of alternative policies and scenarios, e.g., different levels of ambient standards (Chanel et al. 2014; Dias et al. 2012; Heal et al. 2013), to apportion health impacts by source industry (Fann et al. 2013), and to explain the benefits of standards, e.g., the avoided 230,000 premature deaths annually by 2020 due to implementation of $PM_{2.5}$ controls between 1990 and 2005 in the US (US EPA, 2011). At regional (sub-national), urban and project scales, HIAs can be conducted in a policy context, but more commonly to gauge potential impacts and benefits of specific actions. In particular, HIAs conducted by health departments, academic researchers or advocacy groups often aim to incorporate health outcomes in policy and decision making (Dannenberg and Wernham, 2013).

Due to limitations in the scope and available data, most HIAs have been qualitative rather than quantitative (Rhodus et al. 2013). While qualitative assessments can convey the direction and magnitude of impacts, quantitative methods offer more explicit information regarding impacts of potential interventions or the status of abatement policies (Bhatia and Seto, 2011). Several guides for the design and implementation of HIAs have provided recommendations for screening, scoping, and impact assessment steps of the HIA process. However, there are few recommendations for reporting and communicating results (Hebert et al. 2012). Metrics that effectively communicate impacts to stakeholders and decision-makers need to be identified.

Tools developed to facilitate the systematic quantification of impacts produce different metrics. The Environmental Benefits Mapping and Analysis Program (BenMAP) developed by US EPA and the Air Quality Benefits Assessment Tool (AQBAT) used by Health Canada report impacts as attributable cases and monetized impacts (Judek et al. 2006; US EPA, 2015a). Air pollution accountability research tends to favor these metrics (Bell et al. 2011). The Integrated Environmental Health Impact Assessment System developed for the European Union (Briggs, 2008) uses time-based health metrics (e.g., disability adjusted life years, DALYs). Originally developed for the comparative risk assessment framework (Murray, 1994), these metrics summarize different health effects with varying degrees of severity into a single figure (de Hollander and Melse, 2006; Hofstetter and Hammitt, 2002).

Health impacts associated with air pollution vary by duration (chronic or transient), degree (severe or minor) and temporality (caused shortly after exposures or lagged by several years).

Urban-scale HIAs can address projects or policies that affect the entire urban area or a specific segment of the population. Thus, the applicability of the certain health metrics may depend on the boundary of the HIA, the severity of the predicted impacts, and community values regarding health. Previous reviews have discussed differences between qualitative and quantitative HIAs (Bhatia and Seto, 2011; O'Connell and Hurley, 2009), but the types of metrics used in quantitative urban-scale HIAs have not been addressed.

The goal of this chapter is to evaluate quantitative metrics used in HIAs and similar analyses that are relevant to air quality management at the urban and potentially regional scales. The metrics are evaluated using explicit criteria, and demonstrated using a case study that focuses on particulate matter less than 2.5 µm in diameter ($PM_{2.5}$). The chapter concludes with recommendations for those metrics that can best inform decision-makers.

Methods

Literature published between 2011 and 2015 was reviewed to identify HIA metrics used for both project and policy applications. Reviews and critiques of HIAs (in both the peer-reviewed and grey literature) and original peer-reviewed articles were examined, and included studies that evaluated the burden of disease attributable to ambient air pollution, the health benefits of proposed ambient air quality standards, and policies to reduce pollutant levels (e.g., active transport). The HIAs identified in the literature ranged in scale from multi-national to urban. Recent regulatory impact analyses (RIAs) by US EPA were also reviewed (US EPA, 2015b, 2014, 2012a). Selected metrics include the predicted number of cases, time-based metrics, impacts per unit emissions, and monetized impacts.

Evaluative criteria were identified from two sources. First, findings of the reviewed quantitative HIAs were used to identify key characteristics relevant to air quality metrics, e.g., metrics should account for population dynamics since pollution-related health effects can lag years behind exposures (Flachs et al. 2013). Second, review articles and commentaries from the health indicator literature were examined to identify additional criteria, e.g., the comparability of metrics across populations of different size (Walker et al. 2007).

A case study demonstrates the formulation, use, strengths and limitations of the metrics using Wayne County, a mostly urban and suburban region (area of 1600 km^2, population of 1.8 million) with a mix of industrial, commercial, area, and mobile emission sources, as the study area. The county scale was selected due to the availability of emission and other data. A scenario is evaluated in which $PM_{2.5}$ concentrations are uniformly lowered across the county from 10 to 8 $\mu g/m^3$, reflecting a policy that further reduces concentrations below the current national ambient air quality standard of 12 $\mu g/m^3$ (US EPA, 2013a). The analysis follows the method reported by Fann et al. (2012) with several differences. To examine potential differences between HIA methodologies, two methods (detailed below) are used to estimate mortalities attributable to changes in $PM_{2.5}$ levels. In addition to the concentration-response (CR) estimates included in the BenMAP software, cause-specific mortality CR estimates developed for the recent Global Burden of Disease (GBD) study (Burnett et al. 2014; Lim et al.

2012) are used. To assess the sensitivity of results to national, county and local scale data, attributable rates for premature mortality are calculated using baseline rates for the US as a whole, Wayne County (including Detroit), and Detroit separately. To facilitate these analyses, a simple spreadsheet model is used that does not represent spatial differences in air quality, population or impacts across the study area. Uncertainty in the number of avoided cases predicted for the case study is simulated using a Monte Carlo (MC) analysis (@Risk for Excel, Palisade Corporation). For each CR estimate, the distribution around the regression coefficient is specified based on the reported standard error. The simulation uses 5000 iterations to estimate the mean number of avoided cases and to construct 95% confidence intervals around the mean. The uncertainty in the number of avoided cases is propagated to the DALY and monetized impact metrics. Other sources of uncertainty for these summary metrics, e.g., uncertainty in disability weights or monetized values, are not included. Additional information on the case study is found in Appendix A2.

Emissions-based metrics (e.g., benefits per ton) use sector-specific 2011 $PM_{2.5}$ emissions information for Wayne County (US EPA, 2012b). Annual emission rates are listed in Table A2.6. Following source apportionments performed for Detroit (Buzcu-Guven et al. 2007; Gildemeister et al. 2007; Milando et al. 2016), half (5 $\mu g/m^3$) of the initial and existing $PM_{2.5}$ is assumed to arise from local sources (e.g., direct $PM_{2.5}$ emissions from industrial point sources, diesel and gasoline mobile sources, construction and road dust emissions, other non-point sources) that collectively emit approximately 7,000 tons per year; the other half arises from regional sources and the formation of secondary $PM_{2.5}$. Using a “roll-back” method, a 2 $\mu g/m^3$ reduction is achieved by reducing local emissions by 40%, or 2,800 tons per year. While simple, this approach attains results that reflect those from more complex methods that explicitly model sources and spatial variation (described later), and that are suitable for demonstrating the alternative health metrics. The benefits per ton metric is calculated by dividing avoided impacts (e.g., avoided cases and monetized impacts per year) estimated using a health impact function by the emission reduction.

Results

Literature Review

HIA metrics in previous air quality and other studies

HIA applications have been summarized and critiqued in several reviews published in the peer-reviewed and 'grey' literature (Bhatia and Seto, 2011; Dannenberg and Wernham, 2013; Hebert et al. 2012; O'Connell and Hurley, 2009; Rhodus et al. 2013; Schuchter et al. 2014). Many HIAs have been made publically available (Pew Charitable Trusts, 2014; UCLA HIA-CLIC, 2015). The following emphasizes HIAs involving air quality analyses.

Most urban scale HIAs have been conducted for urban planning, transportation, and land use projects. In a review of 81 transportation, housing and infrastructure, land use, and waste management HIAs conducted between 1999 and 2012 in the United States, 52% considered air quality impacts, in part due to the availability of models and other assessment tools, but only 28% used quantitative methods (Rhodus et al. 2013). In contrast, nearly all (37 out of 38) HIAs examined in the peer-reviewed literature used quantitative metrics, and most of these studies

(71%) were conducted outside of the United States. (These studies are summarized in Table A2.1.) Typically, impacts are reported as the number of (avoided) cases attributable to changes in ambient concentration. Fewer studies have reported impacts using DALYs or monetized impacts. Only eight of these HIAs used multiple metrics. Sometimes these metrics were calculated using standardized platforms, e.g., BenMAP. Other metrics in HIAs or regulatory analyses include cost-effectiveness and cost-benefit indicators. A few studies used indicators designed for life cycle assessment (LCA). These metrics are detailed below.

Predicted cases

As noted, the most common quantitative HIA metric is the number of morbidities or premature mortalities attributed to a change in pollutant concentration. The number of predicted cases is calculated using two similar approaches. The population attributable fraction (PAF) method, endorsed by the WHO (Prüss-Ustün et al. 2003), represents the fraction of risk for an outcome attributable to a specific exposure. It is estimated for specific exposure concentrations using concentration-dependent relative risks (RR):

$$PAF = \frac{P_e(RR-1)}{P_e(RR-1)+1} \tag{2.1}$$

where *RR* = relative risk for the outcome, e.g., $e^{\beta\Delta x}$ for a log-linear risk coefficient where Δx = change in ambient concentration, β = the regression coefficient, and P_e = the probability of exposure (i.e., the fraction of the population that is exposed; Steenland and Armstrong, 2006). For air pollution, the PAF is typically used to estimate the burden of disease relative to non-anthropogenic background levels. Multiplying the PAF by the baseline rate in the population (*y_0*, cases person^{-1} year^{-1}) and the number of people in the population (*P*) gives the number of attributable cases in the population. Recently, this approach has been used to estimate the burden of disease attributable to air pollution (Cárdaba Arranz et al. 2014; Hänninen et al. 2014), and to compare $PM_{2.5}$ standards in Taiwan (Yang and Kao, 2013).

The second method uses a health impact function (HIF) to estimate changes in outcome incidence. The HIF represents a simplified PAF where the entire population is considered exposed (e.g., P_e=1). The HIF depends on the form of the CR function, e.g., a log-linear CR estimate gives:

$$\Delta Y = y_0 \left(1 - e^{-\beta \Delta x}\right) P \tag{2.2}$$

where *ΔY* = incremental change in the number of cases, y_0 = baseline incidence rate (cases person^{-1} year^{-1}), β = CR estimate (log relative risk), *Δx* = expected or measured change in concentration (μg/m^3 or ppb), and *P* = exposed population (US EPA, 2015a). The HIF can estimate the incidence attributable to pollution relative to 'pristine' or 'background' levels (Fann et al. 2012b), but generally is used to evaluate incremental impacts associated with a change in concentration, e.g., effects of a new standard relative to existing concentrations (Berman et al. 2012; Boldo et al. 2014; US EPA, 2012a).

Both PAF and HIF methods require information including the size of the exposed population, baseline incidence rates for diseases associated with pollutants, baseline and exposure concentrations, and CR estimates or relative risks for each pollutant-outcome pair. Prospective applications also require projections of population size and baseline rates; retrospective applications need current and historical data. CR estimates are drawn from the epidemiological literature, including large observational studies (e.g., Jerrett et al. 2009; Krewski et al. 2009), as well as smaller studies of targeted populations (e.g., Mar et al. 2004). CR estimates can be chosen from a single study or pooled across multiple studies. 'Counterfactual' concentrations (CFCs) for $PM_{2.5}$ between 5.8 and 8.8 μg/m^3 have been used as comparison or baseline conditions to represent non-anthropogenic 'background' levels (Burnett et al. 2014; Krewski et al. 2009; Murray et al. 2003).

Disability-adjusted life years

Duration metrics consider the time lived with disability or the time lost due to early death, and are derived from the number of predicted cases. Years of life lost (YLL) is the difference between the age-specific remaining life expectancy (LE) and the age of premature death. Years living with a disability (YLD) is the time spent living with a morbidity (i.e., the case duration), weighted by a disability weight (DW) that reflects the degree of impairment as assigned using trade-off methods (Prüss-Ustün et al. 2003), e.g., a panel evaluation where experts judge which hypothetical person with a randomly assigned disease is healthier (Salomon et al. 2012). YLL and YLD are calculated for each population stratum (e.g., age group, sex, or race/ethnicity):

$$YLL_{j,a} = N_{j,a} \times LE_a \quad (2.3)$$

$$YLD_{j,a} = N_{j,a} \times D \times DW \quad (2.4)$$

where $N_{j,a}$ = number of avoided cases in stratum *j* and age group *a*, LE_a = standard remaining life expectancy for age group *a* (in years), D = duration of the disease state (in years), and DW = disability weight for the morbidity outcome. DWs range from 0 (perfect health) to 1 (death).

The calculation of YLLs requires the use of standard life tables to determine the remaining life expectancy for each age group. Life tables can be developed for each year of life and particular age intervals using age-specific mortality rates for the population of interest (Anderson, 1999); this information is available at country and state levels (MDCH, 2015; World Health Organization, 2015).

DALY metrics sum YLL and YLD (eqs. 2.3 and 2.4) across the population, thus aggregating across different outcomes (e.g., asthma exacerbation and premature mortality). DALYs are commonly used in burden of disease studies (Flachs et al. 2013; Hänninen et al. 2014), and have been used in policy evaluations (Rojas-Rueda et al. 2013) and life cycle impact assessments (Kassomenos et al. 2013).

Quality-adjusted life years (QALYs) provide an alternative approach to DALYs. QALYs were developed to provide a comprehensive measure of health in multiple dimensions, e.g., physical health and social well-being (Gold et al. 2002) using weights that range from 1 (perfect health) to 0 (death; Sassi, 2006). Weights assigned to QALYs are not tied to a particular disease status, but rather look at an individual's overall health state. In contrast, DALYs use disability weights that focus on a single disease and comorbidities are not considered (Gold et al. 2002). In this paper, DALYs are used as a summary measure of health given their use in previous studies (Table A2.1).

Monetized impacts

Mortality and morbidity outcomes can be monetized to facilitate cost-benefit and cost-effectiveness analyses. For deaths, valuations often use the value of a statistical life (VSL), a monetary value assigned to a premature mortality based on willingness to pay (WTP), derived as what an individual would pay to reduce their risk of dying in the next year by a small amount, e.g., 1 in 100,000 (Hammitt, 2000). An alternative measure is the value of a statistical life year (VSLY), a value assigned to each YLL rather than to each premature death (Hammitt, 2007). For morbidity, valuations use the WTP or the average cost of an illness (COI), which incorporates medical expenses and societal costs, e.g., lost wages (Akobundu et al. 2006). Valuations can be discounted to account for the time-value of money, e.g., for an assumed 20 year lag between a concentration reduction and premature mortality, US EPA (2012a), suggests apportioning 30% of the mortality in the year following the concentration reduction, 50% in the 2nd through 4th years, and the remaining 20% between 6th and 20th years, and applying discount rates from 3 to 7% per year (OMB, 2003). Valuations without lags represent the "maximum impact" case since all impacts are assumed to occur immediately following the concentration change.

Functional unit-based metrics

Additional health metrics are used in life cycle assessments (LCA), which provide a comprehensive assessment of a product or service. Most LCAs use streamlined approaches that quantify impacts on the basis of a functional unit, e.g., per ton of $PM_{2.5}$ emitted. Characterization factors relate environmental stressors evaluated in an LCA to health outcomes, e.g., the ReCiPe framework defines DALYs per kg of $PM_{2.5}$ emitted (Goedkoop et al. 2009).

Regulatory analyses have used metrics expressed as outcomes per ton of emissions. Such metrics may be advantageous when changes in emissions (rather than ambient concentrations) are estimated, e.g., a rule requiring increased efficiencies for residential wood-burning heaters estimated monetized benefits of $380,000 per ton of $PM_{2.5}$ emissions reduced (US EPA, 2015). This metric was derived using the expected change in emissions, dispersion modeling to estimate concentrations, HIFs to predict avoided cases, and economic valuations to monetize outcomes (US EPA, 2013).

Economic metrics

Economic metrics incorporate health measures along with resource constraints, typically expressed as the cost of implementing a policy or project. For example, cost-effectiveness metrics using benefit-cost ratios can compare monetized benefits, in part derived from HIAs, to expected costs (Johannesson, 1995). Such metrics are sometimes required, e.g., proposed regulation in the US undergo a regulatory impact analysis to demonstrate their cost-effectiveness (US EPA, 2010). The total cost of an air quality management strategy includes the direct expenditures made by polluters, e.g., costs of equipment, operation and maintenance, subsidies and financial incentives, and costs to air pollution control districts for planning, monitoring and enforcement; benefits include all avoided health, social, and environmental impacts (Bower and Brady, 1981). It can be difficult to monetize all benefits of air quality management, particularly for secondary and tertiary impacts, e.g., climate change mitigation; the scope and uncertainty of such analyses can present challenges. In addition, cost-benefit analyses may mask equity concerns given their focus on efficiency and overall costs and benefits rather than benefits to specific groups (de Groot, 1998). Despite their complexity and limitations, cost-benefit analyses can help select effective strategies, particularly for multi-pollutant strategies that may have high implementation costs but substantial health benefits (Chestnut et al. 2006).

The present analysis focuses on health metrics. The $PM_{2.5}$ reduction in the case study might be achieved by a number of management strategies, which would likely vary in costs. Given the study's emphasis, the analysis does not identify a specific strategy and thus does not estimate control costs or calculate economic metrics. While a full discussion of economic metrics utilizing HIAs is beyond the scope of this chapter, guidelines for conducting economic analysis for environmental policy assessment have been presented elsewhere (US EPA, 2010).

Case study

The case study uses a 2 μg/m^3 reduction in $PM_{2.5}$ concentrations to illustrate the health impacts of the health metrics in urban scale air quality HIAs. The metrics could be used to compare control strategies directly, and they might be incorporated into broader environmental impact assessments, such as those specified by the National Environmental Policy Act (Bhatia and Wernham, 2008). As discussed previously, they also are necessary for cost-benefit and cost-effectiveness analyses, although the present paper is limited to an analysis of health impacts. The next section discusses implications for using health metrics in air quality management.

Predicted impacts

HIA results for the case study are summarized in Table 2.1. Additional details are provided in Tables A2.7 and A2.8 in Appendix A2. Lowering $PM_{2.5}$ levels from 10 to 8 μg/m^3 is estimated to prevent 190 premature all-cause deaths, 230 cause-specific deaths (the sum of chronic obstructive pulmonary disease (COPD), lung, trachea and bronchus cancers, ischemic heart disease (IHD), and stroke deaths), 28,000 avoided asthma exacerbations, and 37,000 minor restricted activity days per year (MRAD), i.e., days when individuals avoid typical activities and instead switch to less strenuous tasks without missing work or school. Attributable rates for avoided premature deaths are higher when based on Detroit mortality rates compared to those for all of Wayne County or the U.S. (Table 2.2). Similar distributions of impacts have been reported in the several studies that evaluated both mortality and morbidity outcomes (Berman et al. 2012; Chart-asa and Gibson, 2015; Fann et al. 2013, 2012b; Jakubiak-Lasocka et al. 2015;

Voorhees et al. 2014). All of these studies show that less severe outcomes make up the majority of avoided cases.

Avoided YLL, YLD, and DALYs in the case study total 3052, 47 and 3099 years, respectively (Table 2.3). YLL are greatest for the 60-64 year age group (17 premature deaths contribute 394 YLL; Figure 2.1). Premature deaths account for 98.5% of the total DALYs avoided in the population. Among morbidity outcomes, asthma exacerbations make the greatest contribution to population DALYs (30 YLD per year, Table A2.7). Comparable contributions of YLL and YLD to the overall DALYs have been reported elsewhere (de Hollander et al. 1999; de Hollander and Melse, 2006; Hofstetter and Hammitt, 2002).

The total monetized health benefit of the 2 $\mu g/m^3$ reduction in Wayne County exceeds $1.9 billion annually, most of which (95%) is due to premature mortality (Table 2.3, Table A2.7). The most important morbidity outcomes are non-fatal myocardial infarctions (n=160, $23 million) and unscheduled hospitalizations (n= 150, $5.5 million). More common but less severe outcomes include work loss days (n=21,000, $3 million) and minor restricted activity days (MRAD) (n=37,000, $2.5 million). Though less frequent, hospitalization outcomes account for a large share of the monetized morbidity impacts. The large and dominant contribution of mortalities to the total monetized value parallels the $PM_{2.5}$ RIA (US EPA, 2012) and a recent HIA in China (Voorhees et al. 2014).

For emissions-based metrics, the total monetized benefit (all mortality and morbidity outcomes) is \$660,000 per ton of $PM_{2.5}$, again, mostly due to mortality (\$640,000 per ton; Table 2.4). Expressed using the number of cases, the more severe outcomes had the lowest benefit per ton, e.g., premature mortality were only 0.07 deaths avoided per ton, while avoided asthma exacerbations were 9.8 cases per ton and avoided MRAD were 13.1 cases per ton. The literature shows a wide range but generally lower benefits (\$46,000 to \$510,000 per ton $PM_{2.5}$; Fann et al. 2012a). The higher estimates in the case study likely result from the simplified roll-back approach, which incompletely accounts for distance and dispersion between sources and people, e.g., reductions from elevated stacks and sources farther removed from populations are expected to have lower impacts per ton of pollutant emitted (Fann et al. 2009). Nevertheless, the estimates produced by the case study are reasonable given its limitations, e.g., uniform reduction and rollback approach.

Case study limitations

The case study has a number of limitations. First, the same age-stratified baseline rates are applied across the population, and other sources of variability (e.g., neighborhood, gender) are omitted. Second, the population is held constant. Recent work demonstrates some sensitivity to population growth or mobility (Baccini et al. 2015; Flachs et al. 2013; Tchepel and Dias, 2011). Third, a single CR estimate is used, although other valid CR estimates are available and can be used to represent uncertainties (described later). Fourth, lags and discounting are ignored, which can overestimate premature mortality impacts and further increase the dominance of mortality impacts since YLL estimates are higher for deaths at younger ages (based on life expectancy). Fifth, the exposure scenario does not account for urban scale spatial heterogeneity (Batterman et al. 2014; Sparks et al. 2014), which should be considered to accurately predict impacts (Punger and West, 2013; Thompson et al. 2014). Sixth, impacts due to only $PM_{2.5}$ are considered. Pollution control policies can affect multiple pollutants and have additional impacts and co-benefits. Lastly, both annual and daily concentrations are assumed to undergo the same change (2 μg/m^3), following methods used in other HIAs (Fann et al. 2012b). However, this approach may underestimates changes in daily peak concentrations, which often arise from local sources, and it assumes that the same areas and populations are affected by annual and peak concentrations. Alternately, daily changes in $PM_{2.5}$ and HIFs drawn from studies of short-term exposures could be used to determine short-term health impacts. Despite these limitations, the case study results mirror trends seen in other air pollution HIAs, and the evaluations and comparisons of the different metrics should be valid and applicable to other cities and scenarios.

Evaluation of HIA metrics

The criteria suggested for evaluating HIA metrics (Table 2.5) reflect several goals. First, metrics should be accurate and comprehensive with respect to the overall impacts expected on a population, otherwise impacts may be underestimated and lead to biased evaluations. Second, metrics should consider the spatial and temporal distribution of impacts, thus accounting for the variation in exposure and population susceptibility. This variation, along with equity considerations, will likely require stratification by factors related to individual or group-level susceptibilities, e.g., age, socioeconomic status, or race/ethnicity (O'Neill et al. 2008). Third, since impacts are associated with both short- and long-term exposure to pollutants, and long-term impacts may lag several years, accounting for lags is important. Fourth, metrics should be easily understood by a wide audience, particularly given limited understanding of HIA techniques, pollutant impacts, and the presence of competing interests, e.g., economic or political considerations. Fifth, predicted impacts and valuations in the metrics are inherently uncertain, and uncertainties are propagated as the number of required data inputs increases. Both quantitative uncertainty analyses and descriptive characterizations are needed to describe uncertainties and aid interpretation. The next section contrasts each metric against the evaluative criteria, drawing on case study results to highlight key points. Table 2.6 summarizes this evaluation.

Predicted cases

The inclusion of MRAD, work loss days, and other transient but relatively common morbidity outcomes yields more comprehensive analyses by indicating the numbers of people potentially affected. This can increase the HIA's salience, especially for diseases like childhood asthma that represent important public health issues. The case study (like most other HIAs) included only those outcomes where the weight of evidence for an association is strong. Less evidence exists regarding associations between $PM_{2.5}$ and other outcomes, including cancer and adverse birth outcomes. Following US EPA methods (US EPA, 2012a), these impacts are excluded. Such omissions may lead to systematic negative biases (O'Connell and Hurley, 2009).

The CR function is arguably the most important and most uncertain input in predicting attributable cases. The case study uses a single CR function for most outcomes. Other CR estimates may be valid and available, and can be used to bound expected ranges or show uncertainties, e.g., Fann et al. (2012) noted a 2.5-fold variation in the number of premature deaths using CRs derived from two large multicity observational studies (Laden et al. 2006; RR= 1.16 per 10 μg/m^3 vs. Krewski et al. 2009, RR=1.06 per 10 μg/m^3). This variation may reflect differences in study population demographics, exposure patterns, and other factors. CR estimates should be drawn from well conducted epidemiological studies with sufficient statistical power. For local-scale HIAs, city-specific CR estimates, ideally from large multi-city studies, may be advantageous because they account for specific population characteristics. However, such estimates often are not available. Large multicity cohort studies or meta-analyses can have considerable statistical power, but may not be fully representative of the population for the HIA. When selecting CR estimates for local-scale HIAs, it is important to consider how the original study population differs from the one included in the HIA (Hubbell et al. 2009).

Table 2.2 demonstrates the sensitivity of HIA results to the baseline health data. Compared to national averages (CDC, 2014), attributable rates increase when using data specific to Wayne County (by 18%) and Detroit (by 22%). Thus, the same 2 μg/m^3 reduction yields a larger impact in Detroit given the susceptible population. Using local data in urban-scale HIAs can account for population susceptibility. In addition, baseline health as well as other vulnerability or susceptibility factors are likely to be unevenly distributed across an urban region, e.g., rates of asthma hospitalizations vary 3-fold across the study region and some of the highest rates are seen in more polluted areas (DeGuire et al. 2016). Areas with higher asthma rates are expected to have more avoided asthma exacerbations than areas with lower rates, given the same $PM_{2.5}$ level. The use of spatially-resolved health and exposure data should increase the accuracy of HIA results, and could allow for the development of strategies that target pollutant reductions in areas that confer the greatest benefits

Most (74%) of the cause-specific deaths are due to ischemic heart disease (IHD, Table A2.8). The number of cause-specific deaths avoided (n=230) slightly exceeds the number of all-cause premature deaths (n=190; Table 1). The CR functions used for cause-specific mortality were developed specifically for the latest GBD study (Lim et al. 2012). These non-linear functions were derived from studies examining ambient air pollution, active smoking, secondhand smoke exposure, and cooking smoke exposure (Burnett et al. 2014). The shape of each cause-specific CR curve differs (see Burnett et al. 2014, Figure 2.1), e.g. for IHD, the slope is steeper at lower concentrations and tends to flatten at higher $PM_{2.5}$ levels. At low concentrations (including the 8 to 10 μg/m^3 in the present analysis) where the IHD CR function is steepest, the PAF method gives a higher number of cause-specific deaths than the all-cause deaths estimated by the HIF. Generally, predictions using non-linear CR functions depend on the baseline and scenario concentrations, e.g., lowering $PM_{2.5}$ concentrations from 11 to 9 μg/m^3 avoids 182 cause-specific mortalities (21% fewer deaths than the 10 to 8 μg/m^3 scenario). The numbers of deaths predicted for these concentrations (679 and 498 deaths at 11 and 9 μg/m^3, respectively) exceed those in the original case study (596 and 370 deaths at 10 and 8 μg/m^3, respectively), but differences between the baseline and scenario deaths decreases at higher concentrations. These differences are small compared to uncertainties, as discussed below.

The case study also compared estimates of all-cause mortality predicted by the HIF and PAF methods using the same CR function from Krewski et al. (2009) (Table 2.1). For the specified scenario, the two methods gave the same number of avoided deaths (n=190). Differences between the HIF and PAF methods also result from differences in how health impacts are calculated, i.e., the HIF method uses the concentration difference (Δx = 2 μg/m^3 in the scenario), while the PAF method compares attributable burdens across scenarios (Δx = 10 μg/m^3 – CFC). Thus, lowering $PM_{2.5}$ from 20 to 18 μg/m^3 still gives 190 avoided all-cause premature deaths using the HIF method, but PAF predictions decrease to 176 premature deaths. While these differences are small, the influence on DALYs and monetized impacts is large given the high values assigned to premature mortalities (discussed later).

The HIF (eq. 2.1) in the case study can predict short-term impacts, but with greater uncertainty than for long-term impacts. This paper focuses on changes in long-term (annual average) concentrations, and mortality CR functions based on studies of chronic exposures are used, although the morbidity CR estimates come from short-term exposure studies (Table A2.3). To derive short term impacts, it may be preferable to use mortality CR estimates drawn from short-term exposures studies (e.g., time series studies) with estimates of short-term pollutant concentrations (e.g., daily $PM_{2.5}$ concentrations). As noted earlier, short-term exposures likely will exhibit greater spatial and temporal variation than annual average concentrations, depending on proximity to the local emissions sources, meteorology, and other factors.

Disability-adjusted life years

YLLs, YLDs and DALYs facilitate comparison of impacts among different groups or cohorts in the population. For example, the number of avoided deaths in the 60-64 year age group is 36% lower than avoided deaths in the 80-84 year age group, but the avoided YLLs in the younger group is 62% higher (Figure 2.1). Given the severity of premature deaths (quantified as the YLL), the 60-64 year age group receives the greatest benefit from the $PM_{2.5}$ reduction. YLL may be particularly meaningful for premature mortality since deaths are delayed, rather than avoided (Rabl, 2003).

YLDs tend to deemphasize morbidity outcomes given the short durations of these impacts (e.g., 1 to 5 days) and the small DWs assigned (Table 2.3, Table A2.4). For example, given the duration of an asthma exacerbation (0.005 years) and its DW (0.22), the 28,000 asthma exacerbations avoided annually in the case study contribute only 30 YLDs to the total 3,100 DALYs predicted (Table A2.7). For asthma, estimated YLDs due to emergency department visits or exacerbations may be underestimated since asthma exacerbations are under-reported (Reddel et al. 2009) and the time lost to avoidance behaviors (e.g., not participating in recreational activities) are excluded, potentially biasing HIA results.

This discussion highlights several issues when disparate health outcomes are combined on the basis of duration and severity. In contrast, metrics using the number of cases avoided treat each outcome equally and avoid issues related to subjective weightings (de Hollander and

Melse, 2006). Others argue that consideration of duration and severity is required to make trade-off comparisons between high and low impact outcomes (Wong et al. 2003).

Monetized Impacts

Like DALYs, monetized benefits of air pollution reductions depend on outcomes included, but are driven by mortality, again due to the high value assigned to a statistical life. The VSL used for mortality ($9.6 million) far exceeds values for each morbidity outcomes (Table A2.5). The lack of cessation lags and discounting in the case study is not expected to substantially alter results given the low social discount rates (3 to 7%) recommended (US EPA, 2012a). The valuation method endorsed by US EPA and used in the case study does not monetize deaths based on age using the VSLY or other approaches (unlike the DALYs in the previous section that considered the timing of death in estimating YLLs) (US EPA, 2010). VSL may overstate the value of premature deaths since deaths are delayed, rather than completely avoided. However, VSLY or methods that adjust VSL based on age can raise contentious issues regarding the value of a life saved for older populations (Robinson, 2007), and US EPA has found little evidence to support age adjustments in VSL estimates (US EPA, 2010).

Monetized impacts, like DALYs, deemphasize morbidity outcomes due to their low and uncertain valuations. Morbidity outcomes are difficult to monetize accurately, and the WTP may underestimate the true societal costs. For example, asthma exacerbations account for only 0.08% of the total monetized impacts in the case study, despite being the second-most frequently avoided morbidity outcome (Table A2.7). The value of $58 assigned to each exacerbation (Rowe and Chestnut, 1986) may incompletely account for medical costs or time lost at work or school. Monetized metrics may not reflect the sentiments of affected communities in Detroit and other urban areas where asthma outcome rates greatly exceed state and national norms (DeGuire et al. 2016). The dominance of mortality outcomes has been demonstrated in Shanghai, China where air pollution-related deaths made up 92.5% of total monetized impacts (800 deaths monetized at 1.2 billion yuan compared to 420,000 morbidities monetized at 0.09 billion yuan) (Voorhees et al. 2014). Similarly, US EPA's recent RIA for ozone (O_3) showed that 98% of the total monetized benefits ($2.0 to $3.4 billion) of a 70 ppb ozone standard would be due to avoided premature mortality from both short- and long term exposures (880 to 1,020 avoided deaths) (US EPA, 2014).

Monetized metrics have been used in HIAs to facilitate comparisons among heath- and non-health outcomes. For example, greater utilization of public transport that lowers pollutant levels (due to less personal vehicle use) will increase physical activity (due to additional walking), which promotes health. In a recent assessment of a Boston area proposal to alter transit pricing, the monetized impacts of physical activity ($75 million) far exceeded air pollution’s impacts ($1.5 million) (James et al. 2014). Including the co-benefits of air quality management can provide decision makers with information about the total impact of a strategy on public health, and potentially additional impetus for recommendations. Such analyses can increase the HIA’s scope, complexity and uncertainty, but may be of particular value when the co-benefits are substantial.

Emissions based metrics

Emissions-based metrics are useful when it is more feasible to estimate changes in emissions rather than ambient concentrations, e.g., for a policy that requires the use of a specific control technology. Emission-based metrics also can identify specific emission sources that impose the greatest burden on the population given that contributions from specific sources to local air quality are known. The degree to which a specific source impacts the health of a population depends on a number of factors, including the proximity of the source to the population and local meteorological patterns. In order to use emissions-based metrics effectively, emissions inventory data need to be combined with dispersion modeling, population data, HIFs and the other data described previously (Fann et al. 2009). The case study assumes a 2 $\mu g/m^3$ $PM_{2.5}$ reduction using equal emissions reductions across multiple sectors, does not account for the distribution of sources in the population, and calculates aggregate benefits per ton. The highest benefit per ton of emissions reduced likely will occur for sources or sectors in populated areas that release pollutants near ground level, e.g., on- and off-road diesel engines in densely populated cities. Such analyses can be data intensive and potentially complex, thus data gaps and model uncertainties should be recognized and communicated to key decision makers and stakeholders. In cases, national average values for benefits per ton are available (e.g., US EPA, 2013b). However, each HIA scenario and each city may uniquely influence effects of location-specific characteristics (e.g., location, type, meteorological trends).

Uncertainty in health impact metrics

A simplified uncertainty analysis demonstrates the variability of HIA results due to CR estimates, identified as the single most important source of uncertainty for urban-scale HIAs (Chart-asa and Gibson, 2015). The most uncertain impacts are the low-severity outcomes, as shown by the wide confidence intervals (CIs) for the number of avoided impacts (Table 2.1). The CIs are symmetrical for mortality, respiratory and cardiovascular hospitalizations, emergency department visits, MRAD and WLD since the underlying CR estimates use log-linear models, while asymmetrical CIs result for non-fatal heart attacks and asthma exacerbations since these outcomes are based on logistic regression models. For the latter, the large upper "tail" of the distribution can greatly increase impacts, e.g., the MC analyses for non-fatal heart attacks and asthma exacerbations give means that are 6 and 11% higher, respectively, than the deterministic estimates that use the mean CR estimate (Table 2.1). Large CIs can cause additional issues, e.g., 16% of the MC simulations for asthma exacerbations show disbenefits (negative avoided impacts) when using the HIF estimate in Table A2.3 and a CR function drawn from a single study (Mar et al. 2004). Such implausible outcomes highlight the need to use CR estimates from well-powered studies that have small standard errors, to pool CR estimates among multiple studies, or to truncate negative avoided impacts.

Uncertainty estimates due to parameter uncertainty have been estimated using MC analyses, Bayesian methods, and sensitivity analyses, and a few HIAs have considered uncertainties in model structures (e.g., Baccini et al. 2015; Chanel et al. 2014; Chang et al. 2014; Chart-asa and Gibson, 2015; Woodcock et al. 2014; Xia et al. 2015; reviewed in Mesa-Frias et al. 2013). For the number of avoided cases, uncertainty arises from CR estimate, baseline health outcome rates, and changes in exposure concentrations. These uncertainties are propagated to and potentially increase for other metrics, e.g., as mentioned, additional uncertainties in DALYs include the duration of outcomes and the subjective assignment of disability weights. Similarly, monetized metrics must contend with the subjectivity and variability of valuations. Ideally, uncertainty analyses would consider all sources of variability, including dependencies among inputs. If the total uncertainties among competing mitigation strategies are very large, then quantitative HIAs may not inform the remedy selection, and decisions may rest on economic or other criteria. However, estimates of both health impacts and uncertainties can motivate the need for mitigation, especially if decision makers are risk averse (IOM, 2013). For example, an MC analysis examining health impacts due to vehicle emissions in Chapel Hill, North Carolina (examining uncertainty in CR estimates, $PM_{2.5}$ emissions, exposure concentrations and demographics) gave a substantially higher number of cases compared to deterministic results (Chart-asa and Gibson, 2015). Such uncertainties should be calculated and reported to decision makers.

Quantitative uncertainty analyses themselves have shortfalls. There are substantial data gaps regarding the variability and uncertainty of data, as well as the interactions among variables. Many analyses use a simplified bounding approach that does not indicate the likelihood or confidence intervals of possible outcomes. As mentioned, weight-of-evidence limitations may preclude consideration of potentially important outcomes. For these reasons, characterizing the limitations of the uncertainty analysis itself is important.

Co-benefits of air pollution management

Although excluded in the case study, HIA metrics can incorporate co-benefits of pollution control policies. For example, incentivizing active transportation to replace short car trips reduces emissions and can increase physical activity with significant health benefits (Maizlish et al. 2013). Strategies that promote active and public transportation also decrease the frequency of traffic-related car crashes (Rojas-Rueda et al. 2013; Xia et al. 2015). Increasing tree cover in cities removes pollutants from urban air sheds (Nowak et al. 2013) and can be advantageous for surface cooling and storm water management (Loughner et al. 2012; Wang et al. 2008).

Climate change mitigation and adaptation are major co-benefits of air pollution management. The transportation sector is responsible for 27% of total greenhouse gas (GHG) emissions in the US (US EPA, 2015c) and 23% of CO_2 emissions globally (IEA, 2014). Transportation policies aimed at reducing primary pollutant emissions, particularly those that reduce travel demand or fuel consumption, lead to reductions in GHG emissions (McCollum and Yang, 2009). Comparisons between policy options should consider the health impacts of reduced primary pollutant emissions as well as the environmental and health benefits of reduced GHG emissions.

Co-benefits can be indirect, secondary in nature and long term, and thus difficult to assess. Still, using common metrics to link these outcomes to public health makes the health metrics more comprehensive and compelling. Again, appropriate outreach and education may be required to inform decision makers.

Challenges of the use of quantitative HIA methods

A number of challenges may be encountered when applying the methods in this paper to other regions. First, urban-scale HIAs are best conducted using local baseline health data that reflect the health status of the population (Hubbell et al. 2009). Sub-national health data may not be available where public health resources are limited, e.g., developing countries, especially for morbidity outcomes (Boerma and Stansfield, 2007). Second, most epidemiological studies have been conducted in the USA and Europe where concentrations tend to be lower than other parts of the world, and CR estimates derived from these studies used in other populations have limitations, e.g., while the GBD risk estimates combine several exposure sources, estimates include only mortality outcomes and respiratory infections in young children (Burnett et al. 2014). Third, suitable (e.g., long-term) air quality data for exposure assessment may not be available in many regions. While concentrations can be estimated, e.g., satellite data and global chemical transport models have been used to derive concentrations at coarse spatial resolution (10 km x 10 km, van Donkelaar et al. 2010), such methods also have uncertainties and may not capture urban-scale patterns necessary for local-scale HIAs. Fourth, regions differ with respect to pollutant sources, e.g., vehicle emissions may dominate exposures in the developed countries, while cooking and home heating emissions from biomass combustion may dominate exposures in developing countries. Such differences will shape the nature of control strategies. Due to these and possibly other reasons, site-specific, comprehensive, and quantitative HIAs may not be feasible in some regions. Still, approximations using the approach with surrogate or estimated data may be valuable, and can serve to highlight data gaps.

Recommendations

Several recommendations follow from our analysis of the literature and the case study. First, if requisite data are available, HIAs should use quantitative metrics to assess health impacts and provide meaningful evidence regarding health benefits to decision makers formulating air quality management plans (Fann et al. 2011). Quantitative analyses permit explicit comparisons between options, better characterization of the magnitude of impacts for specific outcomes, estimates of the total number of people affected, and a framing of health outcomes in the same manner as other policy considerations. Quantitative metrics also enable decision makers to more readily incorporate HIA results into the policy process (Davenport et al. 2006). Because they describe concentration-dependent impacts, such metrics allow estimates of benefits for air quality improvements that go beyond standard attainment. The case study example was limited to $PM_{2.5}$ reductions, but multi-pollutant frameworks should be used (Dominici et al. 2010; Johns et al. 2012; Oakes et al. 2014).

Second, since no single metric fully meets the evaluative criteria, the use of several complementary indicators is recommended. The number of cases avoided is simple and easy to interpret, but does not account for the severity of the outcome. To be comprehensive, urban-scale HIAs should report the number of avoided cases for multiple relevant health outcomes, and cases should be disaggregated into subgroups to allow consideration of equity, location, race/ethnicity, age, and other relevant factors. Consideration of multiple health outcomes in quantitative HIAs yields estimates of the total number of people affected, an important indicator itself. However, such estimates may undercount the total number of people affected since not all outcomes are captured. In addition, estimates of morbidity outcomes can have considerable uncertainty, and possible outcomes with limited evidence are excluded. Despite these limitations, inclusion of morbidity outcomes is important for evaluating strategies that may not lead to substantial numbers of avoided deaths, and for minimizing biases that would tend to underestimate the public health impacts. Estimates of morbidity outcomes and the number of people affected should be recognized as "low end" estimates that complement all-cause mortality estimates, and that provide additional information useful for comparing among management options. DALYs incorporate the severity, duration and timing of outcomes, but are complex and require additional data inputs (including uncertain disability weights); moreover, decision makers may not readily understand this metric. Still, DALYs find widespread use in studies of population health, and can aggregate health impacts of policies and programs allowing comparisons across studies. Monetized impacts share many of the same uncertainties as DALYs, and similarly, are driven by mortality, however, these metrics are familiar to decision makers and can be used in other policy evaluations (e.g., cost-benefit analysis). No single summary measure fully captures societal impacts associated with morbidity. Still, HIAs should utilize a composite indicator like DALYs or monetized values that allow ranking of options.

Third, metrics should be tailored to the local context. Some metrics may be particularly useful and favored in certain applications. For example, emissions-based metrics can facilitate comparisons between sectors and between options within a sector, and maybe particularly useful if policy options involve control technologies or if monetized benefits per ton vary considerably by sector and source. Urban-scale HIAs are not limited to an emissions context, and can also be used to inform decision makers about the benefits of alternative exposure reduction strategies, e.g., use of vegetative buffers along highways, rerouting trucks to avoid residential neighborhoods, or use of indoor air filtration. Evidence from quantitative HIAs can encourage decision makers to implement such interventions, especially when the number of people affected is high and the intervention is viewed as cost-effective.

Fourth, community values should be considered in selecting metrics that are appropriate for urban scale HIAs. DALYs and monetized impacts place a high value on mortality. However, morbidity outcomes are far more common. DALYs or dollars might poorly capture local attitudes regarding less severe outcomes, e.g., asthma exacerbations. Engagement with stakeholders at early stages of the HIA would best serve to prioritize outcomes and metrics (Dannenberg et al. 2006). Stakeholder engagement could be achieved using a number of techniques, e.g., community meetings, focus groups, and advisory committees. The choice of which stakeholder engagement strategies are most appropriate will depend on the timeframe of the HIA process, the level at which the decision is made (e.g., local, national) and other factors (NRC 2011).

Fifth, HIAs are strengthened by drawing on local information, including emission and dispersion data, to understand source-receptor relationships, including spatial variability, demographic and vulnerability information, and epidemiological evidence for concentration-response functions.

Sixth, environmental and health co-benefits of air quality management strategies, including climate change mitigation, should be identified. When requisite data are available, these co-benefits should be quantified using the same metrics selected for air pollution health impacts, thus increasing the comprehensiveness of the overall assessment of control strategies.

Lastly, quantitative HIAs may underestimate the total impact of a policy or program because certain environmental or health impacts cannot be reliably quantified. Qualitative methods can augment the quantitative analyses and identify potential health and environmental outcomes that do not have reliable CR estimates, e.g., cancer and adverse birth outcomes.

Conclusions

This study reviewed quantitative metrics in recent HIAs addressing air pollutant exposure, and developed evaluative criteria for selecting and using metrics. The metrics were illustrated in a case study for the Detroit, Michigan area. Quantitative metrics describing the direction, magnitude and severity of expected health impacts can help inform decision makers and elevate health concerns to the level of other political and economic drivers into evaluations of projects, programs and policies. Different metrics prioritize different health outcomes. For examples, the number of avoided cases emphasizes common but lower severity impacts (e.g., minor restricted activity days and asthma exacerbations), while monetized impacts and DALYs emphasize the relatively small number of premature mortalities.

A number of recommendations were developed for selecting metric appropriate for air quality applications. Metrics should be comprehensive, identify the number of people affected for each morbidity and mortality outcome, and clearly communicate both direct and indirect impacts. Further, metrics should use local data (e.g., baseline rates from the study population), incorporate outcomes of high public health importance, and represent the spatial and temporal dimensions of impacts. Uncertainties and limitations should be characterized quantitatively and qualitatively, and reported to decision makers. While appropriate metrics depend on the application, most HIAs would benefit from several metrics that capture impacts to specific population groups as well as overall health impacts.

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Table 2.1. Number of premature deaths and morbidities avoided per year in Wayne County due to a reduction in $PM_{2.5}$ concentration from 10 to 8 $\mu g/m^3$.

Outcome (age group)	Avoided cases[1] (cases per year)	Percent attributable (%)	Attributable rate (per 100,000)
All-cause premature mortality (>29 years, HIF)	190 (130-260)	1.16	10.48
All-cause premature mortality (>29 years, PAF)	190 (120-240)	1.13	10.22
Cause-specific mortality (>24 years, PAF)[2]	230	3.55	12.61
Infant mortality (<1 year)	2 (0-3)	0.77	0.09
Minor restricted activity days (18-64 years)	37,000 (15,000-58,000)	0.44	2,040
Asthma exacerbations (6-18 years)[3]	28,000 (-34,000-76,000)	2.49	12,639
Work loss days (18-64 years)	21,000 (17,000-24,000)	0.92	1,148
Asthma emergency department visit (> 1 year)[3]	190 (49-323)	1.11	86.42
Non-fatal MI (≥ 18 years)	160 (29-260)	4.93	8.92
CV hospitalization (≥ 20years)	84 (56-110)	0.30	4.71
Pneumonia hospitalization (>64 years)	26 (4-47)	0.79	1.45
COPD hospitalization (≥20 years)	25 (15-36)	0.40	1.42
Asthma hospitalization (<65 years)	19 (7-30)	0.66	1.05

[1] Number of avoided cases is rounded to two significant digits; 95% confidence interval in parentheses.
[2] Sum of IHD, stroke, LC and COPD deaths estimated using the PAF method.
[3] Among persons with asthma.

Table 2.2. Rates of premature mortality, years of life lost, and monetized impacts attributable to a reduction in $PM_{2.5}$ concentration from 10 to 8 μg/m^3 based on baseline mortality rates for the United States, Wayne County, and Detroit

Baseline Rate Source	Premature deaths (per 100,000)	Avoided YLL (years per 100,000)	Monetized impacts[1] (1000$ per 100,000)
National	8.6	124.0	83,000
Wayne County (including Detroit)	10.5	163.6	101,000
Detroit	11.0	194.6	105,000

[1] Monetized benefits are in 2010$ projected to a 2020 income level and rounded to the nearest whole number with two significant digits

Table 2.3. DALYs and monetized impacts avoided per year for deaths, unscheduled hospitalizations, and morbidity outcomes in Wayne County due to a reduction in $PM_{2.5}$ concentration from 10 to 8 $\mu g/m^3$. 95% confidence interval in parentheses.

Outcome	DALYs[1] (years)	Monetized impacts[2] (1000$)
Premature mortality[3]	3052 (2011 - 4074)	1,800,000 (1,200,000 - 2,400,000)
All morbidities	47 (-28 - 108)	36,000 (8,900 - 57,000)
Total	3099 (1982 - 4182)	1,900,000 (1,200,000 - 25,000,000)
Percent attributable to mortality	98.5 %	94.8%

[1] DALYs are YLL for mortality outcomes and YLD for morbidity outcomes.
[2] Monetized impacts are calculated using 2010$ projected to a 2020 income level and rounded to the nearest whole number with two significant figures.
[3] Premature mortality is the sum of premature mortality among adults (>29 years, HIF method) and infant mortality (<1 year).

Table 2.4. Benefits per ton for a 2800 tons per year reduction of directly emitted $PM_{2.5}$ in Wayne County.

Outcome (age group)	Avoided Cases (cases per ton)	Monetized Impacts[1] ($ per ton)
All-cause premature mortality (>29 years, HIF method)	0.067	643,845
Infant mortality (<1 year)	0.001	5,364
Minor restricted activity days (18-64 years)	13.058	888
Asthma exacerbations (6-18 years)[2]	9.844	571
Work loss days (18-64 years)	7.346	1,102
Asthma emergency department visit (> 1 year)[2]	0.067	29
Non-fatal MI (≥ 18 years)	0.057	8,173
CV hospitalization (≥ 20years)	0.030	1,247
Pneumonia hospitalization (>64 years)	0.009	334
COPD hospitalization (≥20 years)	0.009	264
Asthma hospitalization (<65 years)	0.007	107
Total monetized benefits		661,442

[1] Monetized benefits are in 2010$ projected to a 2020 income level

[2] Among persons with asthma

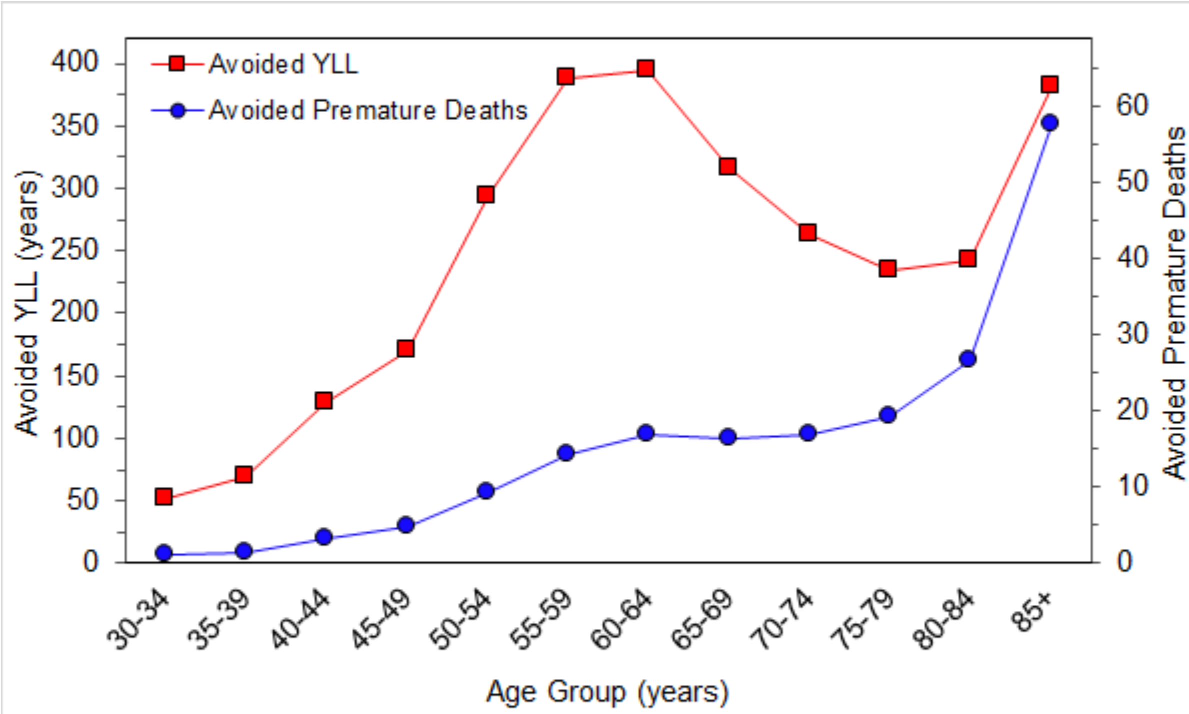
Table 2.5. Criteria used to evaluate potential metrics or urban-scale health impact assessments.

Criterion	Description and Implications	References
Interpretability	Readily understood by lay audiences without need for complex technical explanations	AbouZahr et al. 2007; Murray, 2007; Sanderson et al. 2006
Comparability	Can be compared between different populations, control scenarios or policy alternatives	Walker et al. 2007
Comprehensiveness	Measures the total impact on population health by including all relevant outcomes relevant to the pollutant of interest Considers timing and severity of the outcomes Includes multiple exposure pathways or health determinants (e.g., a public transit policy may reduce air pollution exposures and promote physical activity)	Bell et al. 2011; Rabl, 2003; Wong et al. 2003
Representativeness	Data inputs reflect the baseline health status and demographics of the study population	Bell et al. 2011; Hubbell et al. 2009
Spatial Resolution	Air pollution concentration estimates and baseline health data reflect the heterogeneity in a population's demographics, health status and exposures The boundaries of the HIA are appropriate for the proposed project or policy (i.e., city-wide policies vs. localized projects or programs)	Batterman et al. 2014; Kheirbek et al. 2013; Thompson et al. 2014
Temporal Resolution	Impacts of acute and chronic exposures assessed Accounts for anticipated changes in population (e.g., age structure, baseline rates) over time Considers lag between the timing of exposure and outcome occurrence	Bell et al. 2011; Flachs et al. 2013
Relevant environmental stressors	Considers changes in multiple pollutants and pollutant interactions (e.g., a policy to reduce PM may also influence NO_x or O_3 concentrations which have additional impacts)	Burnett et al. 2005; Dominici et al. 2010
Equity	Disaggregates population subgroups by vulnerability or susceptibility (i.e., race/ethnicity, age, geographic location)	Jerrett et al. 2004; O'Neill et al. 2008
Consideration of uncertainty	Identifies and evaluates uncertainty Uncertainties are communicated effectively	Walker et al. 2007

Table 2.6. Summary of strengths and weaknesses of metrics used in urban-scale health impact assessments.

	Metric	Strengths	Limitations
1a	Predicted number of premature deaths, disease cases or unscheduled hospitalizations e.g., 190 premature mortalities avoided in Wayne county per year	Easy to interpret Demonstrates the magnitude of an impact on a population based on the number people potentially affected Population specific input data lead to estimates that reflect underlying health status and susceptibility to adverse outcomes Stratification based on vulnerability or susceptibility may lead to equity considerations	Comprehensiveness is dependent on the identification and inclusion of all relevant outcomes Dependent on selection of CR and on the baseline rates for outcomes Provides no information on the duration or permanence of the impacts Not all health impacts are independent; can lead to biased estimates if this dependence is not accounted for Cannot be compared directly across populations of differing size
1b	Percent attributable e.g., 1.16% of annual deaths in Wayne County would be avoided	Explains what fraction of the population burden is attributable to air pollution Indicates which option may be more beneficial in reducing the incidence of a specific adverse outcome	Interpretation can be limited if estimates for other exposures are not available for comparison
1c	Attributable rate e.g., 10.5 avoided premature moralities per 100,000 people	Makes metrics comparable between populations of differing size	Rates can be harder to interpret for those unfamiliar with their use (Walker et al. 2007)
2	DALYs	Measures mortality and morbidity in one metric using time as a common unit Accounts for the severity and permanence of an outcome (e.g., duration and disability weight)	Age-weighting and assignment of disability weights can be uncertain or controversial Diminished importance of morbidity outcomes due to weighting factors
3	Monetized impacts	Often used in regulatory analyses and HIAs; can facilitate comparisons with other types of impacts (e.g., economic) Frames health outcomes in the same manner as non-health considerations Facilitate cost-effectiveness or cost-benefit analyses	US EPA methods for monetized premature mortality does not consider the number of years of life lost, only the total number of premature deaths May not accurately reflect the total societal costs of morbidity outcomes
4	Functional-unit based metrics (e.g., benefits per ton)	Appropriate when changes in ambient concentrations are difficult to predict but estimated changes in emissions are available. Can identify emission sources for targeted reductions (e.g., sector specific metrics)	Need to account for the location, proximity to populations, and type of emissions source Impacts (benefits) per ton estimates can be very uncertain depending on the data inputs

Figure 2.1. Number of avoided premature deaths and years of life lost (YLL) per year by age group in Wayne County for a reduction in $PM_{2.5}$ concentration from 10 to 8 μg/m^3.



Appendix A2

SUPPLEMENTAL MATERIALS FOR CHAPTER 2

Wayne County, MI Case Study

As described in the methods, the health impact metrics evaluated in the paper are demonstrated using a case study of Wayne County, MI in 2012.

The study population is stratified into 5-year age groups following 2012 demographics (CDC, 2014). Asthma prevalence among children and adults in Wayne County (2011-2013) is used to estimate the at-risk population for asthma emergency department visits and asthma exacerbations (AIM, 2014). Age- and cause-specific non-injury mortality rates use Wayne County averages for 2012 (CDC, 2014), and hospitalization rates are drawn from the Michigan Resident Inpatient Database (MDCH, 2014). Age-stratified baseline rates for Wayne County were not available for asthma-related emergency department (ED) visits or non-fatal myocardial infarction, so national averages were used (CDC, 2012; Moorman et al. 2012). Baseline incidence rates for asthma exacerbations, minor-restricted activity days (MRAD) and work loss days (WLD) were also not available for Wayne County, so the case study uses rates from the recent $PM_{2.5}$ RIA (Table 5.3, US EPA 2012a). Age-stratified population and baseline health rates used in the case study are listed in Table A2.2.

CR estimates used in the HIF method are drawn from epidemiological studies meeting US EPA criteria which considered sample size, study design and location, and the demographics of the study population (US EPA, 2012a). These CR estimates are either log-linear or logistic and do not vary with age, except for two outcomes. Chronic obstructive pulmonary disease (COPD) hospitalizations and cardiovascular (CV) hospitalization use separate CR estimates for the 20-64 year age groups and the 65+ year age groups. The PAF method uses cause-specific CR estimates for premature mortality developed using a nonlinear function; the CR function decreases with age for IHD and stroke mortalities (Burnett et al. 2014). Specific CRs used are listed in Table A2.3. To contrast the two calculation methods, the PAF method is used to estimate the all-cause mortality burden of air pollution at each scenario concentration relative to the counterfactual concentration (5.8 $\mu g/m^3$) and reports the difference between the two scenarios, and the HIF method is used to estimate the incremental change in incidence due to the change in exposure concentration (Δx = 2 $\mu g/m^3$).

Duration metrics in the case study include YLL and YLD. YLL metrics use age-specific average remaining life expectancies (LE) based on data for Michigan residents in 2012 (MDCH, 2015). Variation in LE due to gender, race, or ethnicity is not considered. Durations of unscheduled hospitalizations use the average length of stay in US hospitals (CDC, 2012). Other outcomes, e.g., asthma exacerbations, work loss days and minor restricted activity days, are assumed to have durations from 1 to 2 days. Disability weights (DWs) for the US are unavailable, and while the GBD group has updated its DW values (Salomon et al. 2012), few air pollution-related outcomes included in the HIA have been assigned DWs. This analysis uses DW values from an analysis comparing health metrics (de Hollander et al. 1999). Durations and DWs are listed in Table A2.4. Outcomes are assumed to occur in the year when $PM_{2.5}$ levels are reduced, i.e., lags are not used. Following the most recent GBD study, DALY estimates are not age-weighted or discounted (Murray et al. 2012).

Because economic valuations specific to Wayne County are not available, dollar values for monetized benefits in the case study follow US EPA values (US EPA, 2010). The currently VLS is derived from 26 studies; VSLY is not currently used. Since WTP for reduced mortality risk depends in part on income, US EPA projected values to 1990 and 2020 income levels (US EPA 2012a), and the case study uses the 2020 values. Values of each incident death or morbidity outcome are listed in Table A2.5.

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Supplemental Tables

Table A2.1. Summary of HIA studies of air pollution reviewed (n=38)

Study	Scope	Scale	Exposures	Outcomes included	Metrics Used
Chart-asa and Gibson, 2015	Project assessment	Urban	Short-term $PM_{2.5}$ (TRAP)	Mortality; hospitalizations	Cases
Hutter et al. 2015	Policy assessment	Urban; Rural	NO_2, PM_{10}, $PM_{2.5}$	Mortality	Cases
Adamkiewicz et al. 2015	BOD	Urban	PM_{10} (TRAP)	Mortality, morbidity	DALYs
Jakubiak-Lasocka et al. 2015	BOD	Urban	$PM2_{2.5}$, PM_{10}	Mortality, unscheduled hospitalizations, other morbidities	Cases
Baccini et al. 2015	BOD	Urban	PM_{10}	Mortality	Cases
Xia et al. 2015	Policy assessment	Urban	$PM_{2.5}$ (TRAP); also physical inactivity	Mortality, morbidity, physical-inactivity related diseases	Cases, DALYs
Chalbot et al. 2014	BOD	Urban	Traffic-related noise, $PM_{2.5}$	CVD and respiratory mortality	Cases
Tobías et al. 2014	BOD	State	$PM_{2.5}$	Non-accidental, CVD, stroke and lung cancer mortality	Cases
Hänninen et al. 2014	BOD	National	O_3, $PM_{2.5}$	Mortality	DALYs
Riojas-Rodríguez et al. 2014	Policy assessment	Urban	PM_{10}, $O3_3$	Mortality, unscheduled hospitalizations	Cases
Cárdaba Arranz et al. 2014	BOD	Urban	PM_{10}, $PM_{2.5}$, O_3	Mortality	Cases
Chang et al. 2014	BOD	Urban	O_3	ED visits for asthma	Cases
Thompson et al. 2014	BOD	Urban	$PM_{2.5}$, O_3	Mortality	Cases
James et al. 2014	Policy assessment	Urban	$PM_{2.5}$	Mortality; Unscheduled hospitalization	Cases, monetized impacts
Woodcock et al. 2014	Policy assessment	Urban	$PM_{2.5}$ (also physical activity, traffic incidents)	Mortality; morbidities	DALYs
Chanel et al. 2014	Policy assessment	National	SO_2	Mortality	Cases, monetized impacts
Voorhees et al. 2014	Policy assessment	Urban	PM_{10}, $PM_{2.5}$	Mortality, unscheduled hospitalizations	Cases, monetized impacts
Boldo et al. 2014	Policy assessment	National	$PM_{2.5}$	Mortality	Cases
Rojas-Rueda et al. 2013	Policy assessment	Urban	$PM_{2.5}$ (also physical activity, traffic incidents	Morbidity outcomes	Cases, DALYs
Punger and West, 2013	BOD	National	$PM_{2.5}$, O_3	Mortality	Cases
Pappin and Hakami, 2013	Policy assessment	Regiona l	NO_x, VOCs	Mortality (short term)	Cases, monetized impacts
Kassomenos et al. 2013	BOD	Urban	PM_{10}, O_3	Mortality (short-term and chronic), Morbidity	DALYs

Study	Scope	Scale	Exposures	Outcomes included	Metrics Used
Heal et al. 2013	BOD	National	O_3	Mortality, unscheduled hospitalizations	Cases
Kheirbek et al. 2013	BOD	Urban	$PM_{2.5}$, O_3	Mortality, unscheduled hospitalizations	Cases
Fann et al. 2013	BOD	National	$PM_{2.5}$, O_3	Mortality, unscheduled hospitalizations, other morbidity outcomes	Cases
Yang and Kao, 2013	Policy assessment	National	$PM_{2.5}$	Mortality	Cases
Flachs et al. 2013	BOD	National	$PM_{2.5}$	Mortality	Cases, YLL, monetized impacts
Vu et al. 2013	BOD	Urban	PM_{10} (TRAP)	Mortality, unscheduled hospitalizations, other morbidity outcomes	Cases
Perdue et al. 2012	Policy assessment	Urban		Changes to environmental determinants of health	None
Dias et al. 2012	BOD	National	PM_{10}	Mortality	Cases
Berman et al. 2012	BOD	National	O_3	Mortality, unscheduled hospitalizations, other morbidity outcomes	Cases
Grabow et al. 2012	Policy assessment	Urban	$PM_{2.5}$, O_3	Mortality, morbidity, physical-inactivity related diseases	Cases, monetized impacts
Rojas-Rueda et al. 2012	Policy assessment	Urban	$PM_{2.5}$	Mortality	Cases
Holm et al. 2012	Policy assessment	Urban	$PM_{2.5}$	Mortality, morbidity, physical-inactivity related diseases	DALYs
Baccini et al. 2011	Policy assessment	Sub-national	PM_{10}	Mortality (short term)	Cases
Rojas-Rueda et al. 2011	Policy assessment	Urban	$PM_{2.5}$	Mortality	Cases
Boldo et al. 2011	BOD	National	$PM_{2.5}$	Mortality	Cases
Tchepel and Dias, 2011	Policy assessment	Urban	PM_{10}	Mortality	Cases

Abbreviations: BOD: burden of disease; DALYs: disability-adjusted life years; NO_2: nitrogen dioxide; NO_x: oxides of nitrogen; O_3: ozone, PM_{10}: particulate matter less than 10 µm in diameter; $PM_{2.5}$: particulate matter less than 2.5 µm in diameter; TRAP: traffic related air pollution; YLL: years of life lost

Table A2.2. Population estimates and baseline health rates by age group for Wayne County, MI used in the case study.

	Population		Mortality rates					Unscheduled hospitalization rates				Other morbidity rates				
Age (years)	Total[1] (n)	With asthma[2] (n)	All-Cause (Per 100,000)	COPD (Per 100,000)	LC (Per 100,000)	IHD (Per 100,000)	Stroke (Per 100,000)	PN (Per 10,000)	COPD (Per 10,000)	Asthma (Per 10,000)	CV (Per 10,000)	ED Visit (Per 100)[3]	Non-fatal MI (Per 10,000)	SB	WLD	MRAD
<1	22758		887.6													
1 to 4	93080	9960										20.8				
5 to 9	118597	12690										9.5		0.076		
10 to 14	125987	13481										9.5		0.076		
15 to 17	128014	13697									33.7	6.5		0.076		
18 to 24	131027	16902							2.6	17.2	33.7	9.1	1.86		0.0054	0.02137
25 to 29	109571	14135	56.58	0.1	0.2	1.4	0.9		2.6	17.2	33.7	8.2	1.86		0.00678	0.02137
30 to 34	109197	14086	82.42	0.1	0.6	3.5	1.7		2.6	17.2	33.7	8.2	1.86		0.00678	0.02137
35 to 39	108669	14018	122.39	0.4	1.3	15.64	3		2.6	17.2	33.7	6.9	1.86		0.00678	0.02137
40 to 44	122813	15843	222.29	1.3	4.4	33.38	5.4		2.6	17.2	198.5	6.9	1.86		0.00678	0.02137
45 to 49	124210	16023	327.67	4.2	13.69	58.77	9.66		51.6	37.6	198.5	6.9	24.9		0.00492	0.02137
50 to 54	132771	17127	603.29	9.79	55.74	119	21.84		51.6	37.6	198.5	6.9	24.9		0.00492	0.02137
55 to 59	125525	16193	975.9	19.92	105.95	262.1	36.65		51.6	37.6	198.5	6.9	24.9		0.00492	0.02137
60 to 64	103861	13398	1411.5	48.14	153.09	360.1	48.14		51.6	37.6	689.7	6.9	24.9		0.00492	0.02137
65 to 69	74641	9629	1889.04	92.44	214.36	484.99	62.97	138.7	157.1		689.7	4.0	81.3			
70 to 74	51462	6639	2827.33	194.32	299.25	623.76	124.36	138.7	157.1		689.7	4.0	81.3			
75 to 79	39937	5152	4146.53	315.5	393.63	833.81	237.87	138.7	157.1		689.7	4.0	81.3			
80 to 84	34075	4396	6761.56	410.86	466.62	1461.48	369.77	138.7	157.1		689.7	4.0	81.3			
≥85	36170	4666	13790.43	624.83	342.83	3212.61	865.36	138.7	157.1		33.7	4.0	81.3			

[1] Population estimates from CDC WONDER, Wayne County 2012 (CDC 2014)

[2] Estimate of persons with asthma is based on the Wayne County asthma prevalence 2011-2013: 10.7% in children and 12.9% in adults (AIM 2014)

[3] Rate is among persons with asthma

Abbreviations: COPD: chronic obstructive pulmonary disease; CV: cardiovascular; ED: emergency department; IHD: ischemic heart disease; LC: lung, bronchus and trachea cancer; MI: myocardial infarction; MRAD: minor restricted activity day; PN: pneumonia; SB: asthma exacerbation (as shortness of breath); WLD: work loss day;

Table A2.3. Concentration-response estimates for each pollutant-outcome pair included the case study.[1,2]

Outcome (age group)	β	SE	Source
Premature Mortality			
All-cause (>29 years)	0.005827	0.000963	Krewski et al. 2009
All-cause (>24 years)	0.014842	0.00417	Laden et al. 2006
All-cause infant (<1 year)	0.003922	0.001221	Woodruff et al. 1997
Trachea, bronchus and lung cancer (≥ 25 years)	IER		Burnett et al. 2014
Ischemic heart disease (≥ 25 years)	IER		Burnett et al. 2014
Cerebrovascular disease (≥ 25 years)	IER		Burnett et al. 2014
COPD (≥ 25 years)	IER		Burnett et al. 2014
Pneumonia hospitalization (>64 years) ICD-9: 480-486, 480-487	0.003979	0.001659	Ito, 2003
COPD hospitalization (20-64 years) ICD-9: 491-492, 494-496 490-496	0.00217	0.000733	Moolgavkar, 2000
COPD hospitalization (>64 years) ICD-9: 491-492, 494-496 490-496	0.00185	0.000524	Moolgavkar, 2000
Asthma hospitalization (18-64 years) ICD-9: 493	0.003324	0.001045	Sheppard, 2003
Cardiovascular hospitalization (20-64 years) ICD-9: 390-429	0.0014	0.000341	Moolgavkar, 2000
Cardiovascular hospitalization (>64 years) ICD-9: 390-429	0.00158	0.000344	Moolgavkar, 2003
Asthma-related emergency department visits (all ages)	0.0056	0.0021	Mar et al. 2010
Non-fatal myocardial infarction (≥18 years)	0.024121	0.009285	Peters et al. 2001
Asthma exacerbations (Asthmatics 6-18 years) as shortness of breath	0.0122	0.0138	Mar et al. 2004
Work loss days (18-64 years)	0.0046	0.00036	Ostro, 1987
Minor restricted activity days (18-64 years)	0.0022	0.000658	Ostro and Rothschild, 1989

[1] Adapted from Fann et al. (2012) Supplemental Materials and US EPA (2015)

[2] Fann et al. (2012) used annual PM2.5 concentrations as a surrogate when assessing impacts due to short-term exposure. The same approach is applied here.

Abbreviations: β: concentration-response regression coefficient reported by each study; SE: standard error

Table A2.4. Duration and DW estimates used in DALY calculations for the case study.

Outcome	Duration (years)	DW	Sources
Premature mortality	YLL	1	MDCH, 2015
Pneumonia hospitalization	0.014	0.64	CDC, 2012; de Hollander et al. 1999
COPD hospitalization	0.012	0.64	CDC, 2012; de Hollander et al. 1999
Asthma hospitalization	0.009	0.64	CDC, 2012; de Hollander et al. 1999
Cardiovascular hospitalization	0.0126	0.71	CDC, 2012; de Hollander et al. 1999
Asthma-related ED visits	0.0027	0.51	de Hollander et al. 1999
Non-fatal myocardial infarction	0.015	0.42	CDC, 2012; de Hollander et al. 1999
Asthma exacerbations	0.005	0.22	de Hollander et al. 1999
Work loss days	0.092	0.0027	Murray, 1994; Ostro, 1987
Minor restricted activity days	0.092	0.0027	Murray, 1994

Abbreviations: COPD: chronic obstructive pulmonary disease; DW: disability weight; ED: emergency department; YLL: years of life lost

Table A2.5. Economic valuations assigned to each incident outcomes

Outcome (age group)	Valuation (2010$)
Mortality (all ages)	$9,600,000
Pneumonia hospitalization (>64 years)	$36,000
COPD hospitalization (20-64 years)	$21,000
COPD hospitalization (>64 years)	$36,000
Asthma hospitalization (<65 years)	$16,000
CV hospitalization (20-64 years)	$42,000
CV hospitalization (>64 years)	$41,000
Asthma ED Visit (all ages)	$430
Non-fatal myocardial infarction (all ages)[2]	$143,000
Asthma exacerbation (all ages)	$58
Work loss days (all ages)	$150
Minor restricted activity day (all ages)	$68

[1]Adapted from US EPA, 2012a. Monetized impacts are estimated using 2010$ projected to a 2020 income level.
[2]Average of the highest and lowest costs at a 7% discount rate
Abbreviations: COPD: chronic obstructive pulmonary disorder; CV: cardiovascular; ED: emergency department

Table A2.6. Direct $PM_{2.5}$ emissions in Wayne County, MI (2011)

Source Sector	Emissions (tons per year)	Percent of Total (%)
Point sources	1610	23
On-road diesel exhaust	725	10
On-road gasoline exhaust	335	5
On-road other	128	2
Non-road other	350	5
Non-road diesel	143	2
Non-point construction dust	18	0
Non-point raved road dust	573	8
Non-point other	3194	45
Total emissions	7,076	100

Source: US EPA 2012b

Table A2.7. Number of avoided cases, DALYs, and monetized impacts per year in Wayne County, MI due to a reduction in $PM_{2.5}$ concentration from 10 to 8 μg/m^3

Outcome (age group)	Avoided cases[2] (n per year)[1]	Percent attributable (%)	Attributable rate (per 100,000)	Rank by number of avoided cases per year	DALYs[2,3] (years)[1]	Rank by number of avoided DALYs per year	Monetized impacts[2,4] (1000$ per year)[1]	Rank by avoided monetized impacts per year[1]
Premature mortality (>29 years, HIF method)	190 (130, 250)	1.16	10.48		2900 (2000, 3900)	1	1,800,000 (1,200,000, 2,400,000)	1
Premature mortality (>29 years, PAF method)	190 (125, 240)	1.13	10.22		2900 (1900, 3,800)	1	1,800,000 (1,200,000, 2,300,000)	1
Infant mortality (<1 year)	2 (0.5, 3)	0.77	0.09		120 (47, 200)	2	15,000 (5,700, 24,000)	3
Minor restricted activity days (18-64 years)	37,000 (15,000, 58,000)	0.44	2,040	1	9 (3.7, 14)	4	2,500 (1,000, 4,000)	6
Asthma exacerbations (6-18 years)[5]	28,000 (-34,000, 76,000)	2.49	12,639	2	30 (-37, 84)	3	1,600 (-1950, 4,400)	7
Work loss days (18-64 years)	21,000 (17,000, 24,000)	0.92	1,148	3	5 (4.3, 5.9)	5	3,100 (2,600, 3,600)	5
Asthma ED visit (> 1 year)[5]	190 (49, 323)	1.11	86.42	4	0.26 (0.07, 0.44)	8	81 (21, 140)	11
Non-fatal MI (≥ 18 years)	160 (29, 260)	4.93	8.92	5	1.0 (0.19, 1.6)	6	23,000 (4,200, 37,000)	2
CV hospitalization (≥ 20years)	84 (56, 110)	0.30	4.71	6	0.75 (0.50, 1.0)	7	3,500 (2,300, 4,600)	4
Pneumonia hospitalization (>64 years)	26 (4, 47)	0.79	1.45	7	0.23 (0.04, 0.42)	9	940 (156, 1,700)	8
COPD hospitalization (≥20 years)	25 (15, 36)	0.40	1.42	8	0.19 (0.11, 0.28)	10	740 (420, 1,000)	9
Asthma hospitalization (<65 years)	19 (7, 30)	0.66	1.05	9	0.11 (0.04, 0.17)	11	300 (110, 480)	10
Total[6]					3100 (2000, 4200)		1,900,000 (1,200,000, 2,500,000)	

[1] 95% confidence interval in parentheses.
[2] Metrics have been rounded to the nearest number with two significant digits.
[3] DALYs are YLL for mortality outcomes and YLD for morbidity outcomes
[4] Monetized impacts are calculated using 2010$ projected to a 2020 income level.
[5] Among persons with asthma
[6] Excludes premature mortality estimated using the PAF method

Abbreviations: COPD: chronic obstructive pulmonary disease; CV: cardiovascular; DALY: disability-adjusted life year; ED: emergency department; MI: myocardial infarction; MRAD: minor restricted activity days; WLD: work loss days; YLD: years living with disability; YLL: years life lost

Table A2.8. Number of avoided cases, DALYs, and monetized impacts for cause-specific mortalities per year in Wayne County, MI due to a reduction in $PM_{2.5}$ concentration from 10 to 8 $\mu g/m^3$.

Cause-specific mortality	Avoided cases[1] (n per year)	Percent attributable (%)	Population rate (per 100,000)	DALYs[1,2] (years)	Monetized impacts[1,3] (1000$ per year)
Ischemic heart disease	170	4.61	9.45	3000	1,600,000
Stroke	23	2.95	1.31	390	220,000
Lung, bronchus and trachea cancer	21	1.80	1.15	360	200,000
Chronic obstructive pulmonary disease	13	1.67	0.71	160	120,000
Total	230	3.55	12.61	4000	2,200,000

[1] Metrics have been rounded to the nearest whole number with two significant digits.
[2] DALYs are YLL for mortality outcomes and YLD for morbidity outcomes
[3] Monetized impacts are calculated using 2010$ projected to a 2020 income level.

Chapter 3

DISEASE AND HEALTH INEQUALITIES ATTRIBUTABLE TO AIR POLLUTANT EXPOSURE IN DETROIT, MICHIGAN

Abstract

The environmental burden of disease is the mortality and morbidity attributable to exposures of air pollution and other stressors. The inequality metrics used in cumulative impact and environmental justice studies can be incorporated into environmental burden studies to better understand the health disparities of ambient air pollutant exposures. This study examines the health burden and disparities attributable to air pollutants for the Detroit urban area. We identify the environmentally attributable fraction of disease burden, apportion this burden to various classes of emission sources and pollutants, and show how the burden is distributed among demographic and socioeconomic subgroups. The analysis uses spatially-resolved estimates of exposures, baseline health rates, age-stratified populations, and demographic characteristics that serve as proxies for increased vulnerability, e.g., race/ethnicity and income. Based on current levels, exposures to $PM_{2.5}$, O_3, SO_2, and NO_2 are responsible for more than 10,000 disability-adjusted life years (DALYs) per year, causing an annual monetized health impact of \$6.5 billion. This burden is mainly driven by $PM_{2.5}$ and O_3 exposures, which cause 660 premature deaths each year among the 945,000 million individuals in the study area. NO_2 exposures, largely from traffic, are important for respiratory outcomes among older adults and

children with asthma, e.g., 46% of air-pollution related asthma hospitalizations are due to NO_2 exposures. Based on quantitative inequality metrics, the greatest inequality of health burdens within the study area results from industrial and traffic emissions. The inequality metrics also show disproportionate burdens among Hispanic/Latino populations due to industrial emissions, and among low income populations due to traffic emissions. These results depend on the study boundaries and consider inequality only within the study area. Attributable health burdens are a function of exposures, susceptibility and vulnerability (e.g., baseline incidence rates), and population density. Because of these dependencies, inequality metrics should be calculated using the attributable health burden when feasible to avoid potentially underestimating inequality. Quantitative health impact and inequality analyses bring value to assessing health and environmental justice considerations in urban settings, and provide important information to decision makers to help prioritize strategies for addressing exposures at the local level

Introduction

Background

Cumulative impact analyses aim to understand the way social and environmental factors combine to increase adverse health risks and impacts across a population (Solomon et al. 2016). This information can identify areas where social and environmental stressors together create environmental justice (EJ) concerns, such as disproportionate impacts and health disparities among low income communities and communities of color (Mohai et al. 2009), often with the goal of helping disadvantaged groups gain access to the resources needed to improve existing conditions (Solomon et al. 2016). These studies often focus on susceptible and vulnerable populations. Susceptibility typically refers to intrinsic factors that tend to intensify the biological response that results from exposure to a stressor, such as advanced age or underlying disease; vulnerability typically refers to extrinsic factors that can increase exposures or reduce the ability to mitigate them, such as living near a pollutant source or having lower socioeconomic status (SES) (O'Neill et al. 2012; Sacks et al. 2011). Disproportionate impacts can result where exposures are high and residents are susceptible or vulnerable.

Cumulative impact analysis frameworks, which are intended to quantify the degree to which segments of the population are disproportionately impacted (Morello-Frosch et al. 2011), have been developed to incorporate several social and environmental hazards, e.g., air pollutants, temperature, high rates of disease, and proximity to hazardous land uses. These studies often use a weighted index or similar metric to combine factors into a single score that can be used to compare burdens across groups. Air pollution is a frequently cited environmental hazard in cumulative impact assessments, e.g., disproportionate impacts from exposures to nitrogen oxides (NO_x), particulate matter ($PM_{2.5}$), and diesel particulate matter (DPM) have been shown at the census tract level for minority populations in California (Su et al. 2012, 2009), and for traffic-related exposures among non-white and low SES populations in Minneapolis (Pratt et al. 2015). Using exposures as a proxy for air pollution health impacts, however, may be problematic for several reasons. First, many cumulative impact studies use poorly-resolved exposure data. For example, estimating exposures using distance-weighted concentrations at the nearest ambient monitoring station (Meehan August et al. 2012) may poorly represent intra-urban gradients in exposure that affect the distribution of impacts (Levy and Hanna, 2011;

Matte et al. 2013). Second, exposures alone do not account for other vulnerability factors that increase the risk of an adverse health impact (Morello-Frosch et al. 2011). These factors are especially important for pollutants that have limited spatial variability, e.g., ozone (O_3); for these pollutants, inequalities will be driven by differences in susceptibility or vulnerability rather than exposure. Other issues with using exposures as a proxy for health risks include the difficulty in assigning weights to pollutants that have different health effects (Sadd et al. 2011), the limited ability to assess exposures to multiple pollutants, and difficulty of identifying culpable sources or source categories.

There is a growing effort to incorporate cumulative impact analyses into regulatory and decision-making processes to advance policy goals and public health initiatives (US EPA, 2016a). One approach is to expand the use of quantitative health impact assessment (HIA) methods to better include equity concerns. Quantitative HIAs combine information on population exposures, baseline health rates, concentration-response functions, and other data to estimate the fraction of health impacts attributable to exposures. HIAs are becoming preferred tools for decision making, and several applications have included ambient air pollution as an important environmental exposure (Rhodus et al. 2013). HIA techniques are routinely used to help set the National Ambient Air Quality Standard (NAAQS; e.g., US EPA, 2010a, 2010b, 2012a, 2014). HIAs for air pollution have estimated the health burden in the U.S. attributable to $PM_{2.5}$ and O_3 exposures, which totals 130,000 premature deaths, 180,000 hospitalizations and emergency department (ED) visits, and 100 million restricted activity days in the USA annually (Fann et al. 2012). HIAs at the local scale, which incorporate more spatially-resolved exposure estimates and data on population susceptibility and vulnerability, have shown that health impacts are not evenly distributed and that socially disadvantaged populations often carry heavier burdens (Fann et al. 2011; Kheirbek et al. 2013). HIAs incorporating spatially explicit analyses of susceptibility and vulnerability factors can identify where pollutants have the greatest impact and which groups are most adversely affected. These analyses could support public health actions aimed at minimizing health burdens attributable to environmental exposures, representing a major transition from current practices that tend to be narrowly focused on compliance with regulations and standards such as the NAAQS.

Objectives

This study examines the health burden and health disparities (or inequities) attributable to air pollutant exposures at the urban scale. Impacts due to five pollutants ($PM_{2.5}$, NO_2, SO_2, O_3, and diesel exhaust particulate matter) are evaluated using HIA techniques and inequality metrics in a spatially-resolved analysis of Detroit, Michigan and neighboring cities. The analysis distinguishes impacts due to different source types, e.g., point (i.e. industrial) and mobile (i.e. on-road traffic) emission sources, and examines the sensitivity of results to spatial resolution and study boundaries.

Detroit and the surrounding communities makes a compelling study location due its density of heavy industry, historically high pollutant levels, and individual and population-level characteristics that increase vulnerability and susceptibility. A portion of the study area has been designated as non-attainment for the SO_2 NAAQS, and the entire area is likely to be designated as non-attainment for O_3 (MDEQ, 2016a, 2016b). Area residents have high rates of diseases associated with environmental exposures, e.g., asthma hospitalization rates in the study area are nearly three times the state average (MDHHS 2014), and characteristics that increase their vulnerability to air pollutants, including proximity to industry, lower educational attainment, high rates of poverty, and linguistic isolation (Schulz et al. 2016). The study approach and many results are applicable to other EJ and cumulative impact analyses as well as environmental policy-making.

Methods

The health burden and disparities analyses use exposure information derived from air quality monitoring and dispersion modeling, quantitative HIA techniques, and inequality metrics, elements described below. Additional details are in Appendix A3.

Study area, spatial resolution, and study population

The study area encompasses Detroit and the adjacent cities of Hamtramck, Highland Park, River Rouge, Ecorse, Lincoln Park, Melvindale, Dearborn, and Allen Park (Figure 3.1). This area has a total population of 945,000. Across the entire study area, 66% of residents identify as Black or African American, 7.3% identify as Hispanic or Latino, and 37% live below the poverty level (US census Bureau, 2014). In Detroit, the largest city in the study area, more than 92% of the population is non-white: 82.7% identify as Black or African American and 7.8% identify as Hispanic or Latino (US Census Bureau, 2015a). Across the study area, demographics and poverty status vary. The percentage residents who identify as persons of color ranges from 12.5% in

Allen Park to 94.2% in Highland Park, and the percentage of persons in poverty ranges from 7.2% in Allen Park to 48.5% in Hamtramck (US Census Bureau, 2014). The percentage of the population that are persons of color is higher in the study area (75.6%) than in Wayne County (50.2%) and the state of Michigan as a whole (23.9%) (US Census Bureau, 2014). Similarly, the percentage of the population that lives below the poverty level in the study area (36.8%) is higher than in Wayne County (24.8%) and the state as a whole (23.7%).

Selection of the study boundaries is based on several considerations. First, we focus on cities in southeast Michigan which may have higher exposures as a result of close proximity to industrial facilities and major highways or higher degrees of vulnerability and susceptibility, e.g., higher percentages of minority populations or populations in poverty; these cities have potentially high health burdens due to air pollutant exposures. Second, we use the municipal boundaries of each city to reflect the domain within which local decision makers may act. Third, the dispersion models used (discussed later) are computationally intensive, and modeling larger study areas at a fine spatial resolution (≤1 km) can be impractical. Thus, the analysis focuses on the most heavily impacted cities in the Detroit metropolitan area. (Potential differences in the inequality metrics arising from the use of different geographical boundaries are examined in the Discussion section of this chapter.)

Census blocks are selected as the unit of analysis for the exposure, health, and inequality metrics given the need to balance fine-scale exposure gradients with the availability of population and baseline health data, which is typically available only at coarser resolution, e.g., ZIP codes (Batterman et al. 2014b). Exposures are based on residential location, following epidemiological studies from which the HIA concentration-response coefficients (discussed below) are drawn. Census block-level population data are taken from the 2010 census TIGER/Line shapefiles (US Census Bureau, 2015b). Block-level age-specific subgroups are estimated using the age distribution of the census block group based on the most recent 5 year estimates (2010 – 2014) of the 2014 American Community Survey (ACS) (US Census Bureau, 2014).

Health impact assessment

The numbers of mortality and morbidity cases attributable to air pollution exposures are estimated using health impact functions which use baseline incidence rates, census block-level air pollutant concentrations, and concentration-response coefficients (Martenies et al. 2015). Conclusions of the most recent Integrated Science Assessments (US EPA, 2008, 2009, 2013, 2016b, 2016c) are used to select only those outcomes with established causal links. Exposure thresholds are not used because reliable population-level thresholds have not been identified in the epidemiologic literature (e.g., Bell et al. 2006; Daniels et al. 2000; Schwartz et al. 2008). The excess cancer risk attributable to diesel particulate matter (DPM) is estimated using methods described by Propper et al. (2015). Annual and daily concentrations are used in health impact functions, following the exposure estimates used in the original epidemiology studies, and annual concentrations are used in the estimates of excess cancer risk. Additional details on outcomes, concentration-response coefficients, and baseline outcome rates are presented in Appendix A3.

The health burden is quantified using three metrics: the number of incident cases of mortality or morbidity attributable to pollutant exposure (attributable cases); disability-adjusted life years (DALYs); and monetized impacts. DALYs and monetized impacts are derived from the number of attributable cases. DALY calculations require a disability-weight (DW) and duration (D) for each outcome (Murray, 1994). Health impacts are monetarized using valuations in the most recent $PM_{2.5}$ standard analysis (US EPA, 2012a) and reported in 2010 dollars projected to a 2020 income level. DW, duration, and monetized values are in Appendix A3.

Exposure assessment

Spatially-resolved and current exposures of $PM_{2.5}$, O_3, NO_2, and SO_2 are estimated using air quality monitoring and dispersion modeling. Contributions from regional, point, mobile, and area sources are broken out separately.

Ambient air quality monitoring data from the US and Canada for 2011-2015 were retrieved from U.S. and Canadian monitoring networks (Ontario MECC, 2016; US EPA, 2016b). For $PM_{2.5}$, we use 12 sites in the Detroit area; two Canadian sites are excluded due to differences in measurement methods. For O_3, we use six sites in Detroit and two sites in Canada. Five of the six US sites collected data only during the April to September period. Missing cold season hourly data at the five warm-season monitors are derived from data collected at the Allen Park site (US) and the two Canadian sites using multiple imputation with predictive mean matching in R (van Buuren and Groothuis-Oudshoorn, 2011). NO_2 data are taken from five sites in Detroit and two in Canada, including two near-road sites. For SO_2, two monitoring sites in the US and two in Canada operated throughout the study period; four additional sites around the Marathon Refinery collected data from 2014 onwards. Data from the year 2012 are used in the exposure assessment to coincide with the point and mobile source emissions inventories (discussed below).

Air quality dispersion modeling complements the exposures information provided by the monitoring data. Point source emissions of $PM_{2.5}$, SO_2, and NO_x are taken from the Michigan Air Emissions Reporting System (MAERS; MDEQ, 2001) and the National Emissions Inventory (NEI; US EPA, 2012b). The 5-year average emission rate is used except for a few facilities that experienced large and known changes; these cases used the most recent years. Block-level concentrations of $PM_{2.5}$, SO_2, and NO_x from point sources are estimated using the software package Framework for Rapid Emissions Scenario and Health impact Estimation (FRESH-EST) (Milando et al. 2016a), which uses a pre-computed source-receptor transfer coefficient matrix from the AERMOD dispersion model (Cimorelli et al. 2005), local meteorology, and an adaptive receptor grid (200 m spacing near major sources, and 1 km spacing elsewhere). For major sources (>100 tons yr^{-1}), emissions are modeled at the stack level; other sources are modeled at the facility-level using representative stack parameters. Receptor concentrations are interpolated using inverse distance weighting to a 25 m raster that covers the study area, and block-level concentrations are estimated as areal averages of overlapping raster cells. Concentrations are predicted at the hourly level and averaged to the daily and annual periods used by the health impact functions. For NO_2, we assume that all NO_x is converted to NO_2.

For SO_2, point source emissions account for nearly all emissions in the study area (US EPA, 2012b, 2016e), and background levels are very low. We use FRESH-EST to estimate daily SO_2 exposures in 2012, and monitoring data are used to understand the extent to which FRESH-EST correctly predicts this pollutant. The health impact functions use baseline health rates that do not vary temporally; therefore, the primary concern is whether the modeled SO_2 data represent the distribution of measured concentrations well, not if they have perfect temporal concordance. Distributions of estimated and observed daily mean SO_2 concentrations at the Southwestern High School (SWHS, which triggered the non-attainment status for a portion of southeastern Michigan) and the four closest FRESH-EST receptors (all within 200 m of the monitoring site) show no statistically significant differences (Kolmogorov-Smirnov test, all p values < 0.05; Figure A3.3). While the highest concentrations (over 85^{th} percentile, Figure A3.3) measured at the SWHS monitor are under-predicted, overall, the modeled results provide acceptable estimates of SO_2 exposures for the study population, a conclusion based on non-significant differences between the distributions of modeled and measured concentrations.

Mobile source contributions to $PM_{2.5}$, NO_x, and diesel particulate matter (DPM) are estimated using the RLINE dispersion model (Snyder et al. 2013), a detailed link-based emission inventory for Detroit developed using the MOVES emissions model (US EPA, 2015a), 6900 receptors, and hourly meteorology. Due to the computational burden, every 6^{th} day in 2012 is modeled. We use the same areal averaging methods from the FRESH-EST framework to estimate daily average block-level concentrations (Milando et al. 2016a). As for point sources, complete conversion of NO_x to NO_2 is assumed, which may overestimate NO_2 near major roads.

Apportionment of exposures to source categories

Exposures are apportioned into regional, local, point, mobile, and area source categories. Point and mobile source exposures, which are estimated using dispersion modeling described earlier, and area source exposures are spatially resolved.

Exposures due to "regional" sources, representing long-range transport and secondary formation of $PM_{2.5}$, NO_2, and O_3, are based on monitoring data, and all blocks are assigned the same daily regional concentration. For $PM_{2.5}$ and NO_2, the daily "regional" component of exposure is defined as the second lowest concentration in the monitoring network on that day. The second lowest concentration is usually similar to the lowest, but it avoids possible anomalies associated with possibly erroneous or unrepresentative measurements. For O_3, a secondary pollutant without direct primary emissions, the "regional" exposure is the average across all monitors in the area. This is supported by ambient monitoring that typically shows only modest changes in O_3 levels across the study area.

"Local" exposures of $PM_{2.5}$ and NO_2, representing the fraction of these pollutants that come from local sources, including point, mobile, area, and secondary formation, are estimated from monitoring data. The "local increment" is estimated as the highest daily mean across the monitoring network minus the "regional" estimate. For $PM_{2.5}$, the local increment is spatially resolved by assigning near road blocks (within 200 m of a major freeway) the full local increment; this accounts for local $PM_{2.5}$ emissions not included in the dispersion model (e.g., secondary formation or dust) that are higher in the near-road environment; more distant blocks are assigned half of the increment. This approach is justified by the current emissions inventory, which shows that mobile sources account for approximately 50% of the $PM_{2.5}$ emissions in Detroit (US EPA, 2016e), and by receptor modeling results that show 15 to 30% of $PM_{2.5}$ is due to diesel exhaust and other mobile sources (Milando et al. 2016b).

Estimates of area sources are included in the emissions inventory, but these lack spatial and temporal resolution, and uncertainties may be high, especially for fugitive dust. Rather than model area sources based on these uncertain emissions inventories, we estimate “area” exposures as the “local” source exposures minus the point and mobile source exposures at each census block. Any local exposures not accounted for by the point and mobile source dispersion models are captured in the “area” exposures.

A complete dataset is obtained using days for which both monitoring and modeling results are available. This results in 48 of 61 possible days modeled in 2012. Daily exposures are estimated by drawing from the distribution for complete days, and used in the health impact functions.

Inequality metrics

Inequality of exposures and attributable health impact risks are evaluated at the census block. Risks are evaluated as the risk of a DALY per year, which allows impacts to be summed across health outcomes and age groups while accounting for differences in the frequency and severity of outcomes. Two inequality metrics are used. The Atkinson Index (AI), which assesses inequality across census blocks using the average health impact risk as a reference group (Harper et al. 2013), was originally developed for income inequality; more recently, it has been applied to air quality impacts (Fann et al. 2011; Levy et al. 2009, 2007). The AI includes a subjective "inequality aversion" parameter, which is set to 0.75 following earlier work (Fann et al. 2011). The second inequality metric, the concentration index (CI), evaluates how ambient concentrations and health burdens are distributed across units (e.g., individuals or census blocks) ranked by demographics or socioeconomic status (O'Donnell et al. 2008). Negative CI values indicate that less socially advantaged groups carry heavier burdens. Prior cumulative impact assessment work applied this metric to environmental hazards, including ambient air pollutant exposures (Cushing et al. 2015; Sadd et al. 2011; Su et al. 2012, 2009).

The spatially-resolved demographic and vulnerability measures used by the CI are drawn from block group-level data in the 2014 5-year American Community Survey (US Census Bureau, 2014), specifically: percentages of the population that are non-white, identify as Hispanic or Latino, are persons of color, are foreign born, and with less than a high school diploma; percentage of households with past year income below the poverty level; and median household income (in inflation-adjusted 2014 dollars). The block-group SES variables are downscaled to the block level. (These are mapped in Appendix A3.)

The sensitivity of the inequality analysis results to study boundaries and spatial resolution is examined using additional analyses. The full study domain (493 km^2, 945,000 persons) is compared to a subdomain in southwest Detroit (79.5 km^2, 131,000 persons, Figure 3.1), selected as it contains a large number of major point sources and heavily trafficked roads; this area also has been designated as non-attainment of the SO_2 standard. Both the original study area and the subdomain are within the modeling domain for the point and mobile source dispersion models. For spatial resolution, health and inequality impacts at block- and ZIP code-level are compared. ZIP codes are selected as the unit of comparison in the sensitivity analysis because they are the smallest unit for which health data are available.

Results

Daily population exposures at the census block level

NO_2 and O_3 concentrations show the expected seasonal variation, e.g., daily NO_2 concentrations peak in winter and daily 8-hour maximum concentrations of O_3 peak in summer, while daily $PM_{2.5}$ levels remain relatively consistent. Long term trends in average concentrations (2011-2015) are not apparent based on linear regression of the daily metrics (Figure A3.4).

Daily $PM_{2.5}$ exposures are dominated by regional sources, which contributed an average of 8.3 $\mu g/m^3$ across the study area, compared to 2.9 $\mu g/m^3$ for point, mobile and area sources combined (Table 3.1). DPM accounts for most (90%) $PM_{2.5}$ from on-road mobile sources. For $PM_{2.5}$ and NO_2, average concentrations from on-road mobile sources (0.6 $\mu g/m^3$ and 10.2 ppb, respectively) exceed those from point sources (0.5 $\mu g/m^3$ and 1.4 ppb, respectively). On-road mobile sources account for an average of 42% of NO_2 exposures at the block level. In contrast to $PM_{2.5}$, NO_2 and O_3, only point sources contribute to SO_2 exposures.

Burden of disease

Exposures to O_3, $PM_{2.5}$, SO_2, and NO_2 result in just over 10,000 DALYs per year incurred by residents of Detroit and the adjacent cities; this represents over $6.5 billion annually in monetized impacts (Table 3.2). The fraction of mortalities and morbidities attributable to air pollutant exposures varies by outcome. We estimate that 5.5 and 1.5% of annual deaths are attributable to $PM_{2.5}$ and O_3 exposures, respectively, which is comparable to previous estimates of attributable health burdens in the U.S. (Fann et al. 2012). For morbidities, attributable fractions range from 1.6% of cardiovascular disease hospitalizations to 37% of ED visits for asthma. The sum of regional, point, mobile, and area source impacts is about 6% lower than impacts for (total) exposure of $PM_{2.5}$ and NO_2 due to nonlinearities in the health impact functions. Most of the health burden is due to premature mortality caused by O_3 and $PM_{2.5}$ exposures (140 and 520 deaths per year among adults over 29 years of age, respectively). The most frequent attributable outcomes are minor restricted activity days (760,000 per year), missed school days (570,000 per year), and work loss days (59,000 per year); these impacts are also driven by O_3 and $PM_{2.5}$ exposure. Asthma exacerbations among children, which are linked to all four pollutants, are also common. Air pollutant exposures account for 3,300 emergency department (ED) visits for asthma each year, largely driven by associations with O_3 and NO_2. $PM_{2.5}$ and O_3 account for most of the attributable cases of the health outcome examined. The exceptions are COPD hospitalizations and days with one or more asthma symptoms, which are driven by NO_2. The burden attributed to mobile sources, which exceeds that of point sources, is driven by premature mortality from $PM_{2.5}$ and asthma-related health impacts from both NO_2 and $PM_{2.5}$.

The excess cancer risk from DPM exposure averages 417 (SD = 199) per 10^6 per year, and ranges from 0 to 1,500 per 10^6 per year at the block level. Our results are based on an average DPM concentration of 0.5 μg/m^3 (range: 0 – 2.6 μg/m^3) across all census blocks in the study area. Similar results have been reported in California: for a state-wide average DPM concentration of 0.58 μg/m^3 in 2012, the excess cancer risk was 520 per 10^6 residents per year (Propper et al. 2015). Excess cancer risks are highest in downtown and southwest Detroit where annual average DPM concentrations are highest (Figure A3.5).

Spatial distribution and inequality of exposures and attributable health burden

Health burdens attributable to air pollution exposure are unevenly distributed across the study area, and source categories show large differences. Regional sources show the least variation in health burdens (Figure 3.2B), as expected, and variation is entirely due to differences in at-risk populations and baseline health rates. (Regional $PM_{2.5}$, O_3, and NO_2 exposures are assumed to be homogeneous across the study area.) Point source emissions show the heaviest burdens in central and southwest Detroit, reflecting the dispersal of point source emissions largely occurring in southwest Detroit (Figure 3.2C). Mobile sources make their largest impacts near major roadways, especially interstate highways with a large fraction of heavy duty diesel trucks, reflecting the sharp gradients in concentrations near roads (Figure 3.2D). (Maps of health impacts due to individual pollutants are included in Appendix A3.)

Atkinson Index

Table 3.3 contrasts AI values for exposure concentrations (left) and health risks (right); these quantify the spatial variation seen in Figure 3.2. Inequality in exposure concentrations measured by the AI (0.003 to 0.130) is lower than those for health impact risks (0.040 to 0.245). Inequality is lowest for total exposures to $PM_{2.5}$ (AI = 0.003) and NO_2 (AI = 0.009) because these pollutants are dominated by regional sources that produce similar exposures across the study area (Table 3.2). In contrast, AI values for $PM_{2.5}$, NO_2, and SO_2 from point and mobile sources are higher (e.g., point source exposure AIs are 0.101, 0.034 and 0.064 for $PM_{2.5}$, NO_2 and SO_2, respectively; mobile source exposure AIs are 0.079 and 0.084 for $PM_{2.5}$ and NO_2, respectively) because the dispersion models represent spatial variability and small-scale variation. These results demonstrate the importance of using methods that account for exposure variability at the intra-urban scale; otherwise, key factors that influence vulnerability may be missed.

The inequality of health risks is especially apparent for some pollutants and sources, e.g., $PM_{2.5}$ (AI = 0.126 and 0.126 for point and mobile sources, respectively), NO_2 (AI = 0.159 and 0.191, respectively), and point sources of SO_2 (AI = 0.155). AI values for the health risks (0.040 to 0.245) are considerably higher than those for exposures (0.003 to 0.130), because they account for spatial variability in exposures and baseline health risks and temporal variability in exposures. Temporal variability in exposures, which affect health impact estimates, is not well captured by averaging exposure concentrations over the full year. Including spatial variability in health risks and temporal variability in exposures is important for capturing the distribution of burdens across the population; similar exposures, whether daily or averaged over a year, in two areas with differing baseline health risks will result in unequal health burdens that are not represented by exposures alone. This contrast between inequality in exposures and health risks is especially evident for total exposures to $PM_{2.5}$ and NO_2. For point and mobile sources of these pollutants, the AI for health risks is 1.24 and 4.6 times higher than the AI for exposures; for total exposures, the AI is 13 and 15 times higher. For NO_2, accounting for the distribution of baseline health risks across the population increases the AI from 0.009 for exposures to 0.137 for health risks. Without accounting for the underlying susceptibility of the population at the intra-urban scale, inequality in attributable health burdens due to these pollutants is underestimated, and this underestimate may lead to differing conclusions about which pollutants result in the highest degree of inequality across the population.

The AI results depend on spatial resolution. While results depend on pollutant and source, AI values for exposures and health risks at the ZIP code level averaged 17 and 47% lower, respectively, than values at the census-block level (Table 3.3). Larger spatial units are less likely to capture gradients in exposures and other risk factors that can increase contrasts. Interestingly, the AI value increased in one case: point source emissions of $PM_{2.5}$. This is because the highest annual average point source concentrations of $PM_{2.5}$ are found in a relatively small area near the sources (Figure 3.3A), and this variation still is represented at the

ZIP code level. Although AI values tend to be lower at the ZIP code level, many of the inequality patterns remain.

AI results show sensitivity to both region and pollutant. In the sub-region (defined by the SO_2 non-attainment area), effects on AI values for health risks vary by pollutant and source, but values tend to decrease (Table 3.3). For example, AI values for SO_2 decrease by 33 and 25% for exposures and health risk, respectively, in the sub-region. Most of the excluded area has low SO_2 exposure, but some highly burdened areas remain (Figure A3.6C). In contrast, AI values increase for point and mobile sources of $PM_{2.5}$ because the sub-region contains blocks with low burdens from these sources (Figure 3.2C) and excludes more highly burdened groups in Detroit. These analyses suggest the need for small spatial units (i.e., census blocks) that can capture exposure gradients, and study areas large enough to capture the full distribution of health impacts.

Concentration Index

CIs vary by pollutant, source type, and demographic or SES characteristics (Table 3.4), reflecting the spatial variability of exposures, health impacts, and population subgroups. (CI for pollutant exposures is shown in Table A3.3). The most negative values, indicating the greatest inequality, occur for point source emissions when blocks are ranked by the percentage of residents who identify as Hispanic or Latino (CI x 100 for health risks from point source emissions of $PM_{2.5,}$ SO_2 and NO_2 are -11.7, -13.3 and -9.3, respectively). Other variables with high CI values include percentage of the population with less than a high school diploma, and the percentage foreign born, which are moderately correlated (r = 0.42 and 0.47) to the Hispanic or Latino percentage (Figure A3.7). Many Hispanic and Latino residents live near locations where point sources make major impacts (Figure 3.3C). However, disproportionate impacts are obscured when Hispanic or Latino residents are grouped together with other minority groups in a single "persons of color" variable, which makes up most of the study population (Figure 3.3D), resulting in lower contrasts between risks for the most- and least- advantaged census blocks. Mobile source emissions also result in high CI values for rankings by income (median income and percentage of households below the poverty level). In the U.S., persons earning below the poverty level are more likely to live close to major roads and thus experience higher exposures to mobile source emissions, compared to whites and more affluent groups (Boehmer et al. 2013; Tian et al. 2013).

The CI appears more sensitive to study boundaries than to spatial resolution (Table 3.4). Using ZIP code level data, increased inequality is suggested for some variables, e.g., Hispanic and Latino populations, but the same groups with the heaviest burdens are identified, suggesting that larger scale data may capture inequality effects when they are representative of population trends. However, in the study sub-region, inequality is associated with different characteristics, e.g., the percentage of the population that identifies as persons of color is associated with disproportionate burdens from point source emissions. Disproportionate impacts for non-whites can be more pronounced if the fractions of socially advantaged and disadvantaged (i.e., white and non-white) populations are more equal. Like the AI analysis, these results suggest the importance of the study boundary, the need to include exposed populations, the use of spatial units small enough to represent demographics and exposures and, in addition, whether the characteristics used to identify disproportionate groups are appropriate for the study area.

Discussion

The burden of disease and inequality assessments show that ambient air pollutant exposures can result in significant health impacts for study area residents and contribute to environmental inequalities. Five trends are highlighted for further discussion. First, exposure to air pollutants imposes a substantial health burden, even where concentrations fall below the national standards (NAAQS). Second, impacts are unevenly distributed and depend on pollutant, source type, and spatial patterns of exposure, susceptibility, and vulnerability. Third, ambient monitoring data alone is insufficient to capture the small scale variation in exposures that affect health burden and inequality analyses. Fourth, exposures as a proxy of health risks will underestimate inequality, which may hinder prioritization of strategies to alleviate health disparities. Lastly, health impact and inequality metrics depend on study boundaries and spatial resolution. These results are specific to the study area, but most findings appear applicable to other urban areas.

Burden of disease attributable to ambient air pollutant exposures below the NAAQS

The burden of disease due to pollutant exposure is significant. As noted, a portion of the study area is considered in non-attainment with the SO_2 standard, and the entire southeast Michigan region may be designated in non-attainment with the O_3 standard (MDEQ, 2016a, 2016b).

However, the area is in compliance with the $PM_{2.5}$ and NO_2 standards, and $PM_{2.5}$ is estimated to cause most (97%) of the health burden (9,800 DALYs per year, $5.1 billion per year). This estimate assumes no concentration threshold below which health effects are not expected, which is supported by recent studies showing risks below the current NAAQS, e.g., premature mortality due to $PM_{2.5}$ (Schwartz et al. 2017; Shi et al. 2016). Despite uncertainty regarding impacts of low dose exposures, continued reductions in ambient pollutant concentrations are likely to yield health benefits (Goodkind et al. 2014; Pope et al. 2015). Health burden studies can help guide local, state, or national actions to further reduce concentrations, even in areas meeting current regulatory standards. Substantial benefits could be achieved by focusing on pollutants which are subject to air quality management actions in the study area. For example, NO_2 emissions, which are an O_3 precursor and involved in secondary PM formation (Meng et al. 1997), are likely to be targeted in a future O_3 State Implementation Plan (SIP). Reducing NO_2 emissions can yield large health benefits due to lower concentrations of secondary $PM_{2.5}$ and O_3 (Sacks et al. 2015; US EPA, 2010b). In Detroit, in addition to its role on O_3 formation, reducing traffic emissions of NO_2 also would reduce health inequalities associated with exposure to NO_2 (Tables 3.3 and 3.4).

Intra-urban inequality in the health burden attributable to ambient air pollution

The burden and inequality associated with point and especially mobile sources is striking, resulting in the highest health burden and disproportionately impacts on Hispanic or Latino and low income communities within the study area. This conclusion reflects the pollutant dispersion from tall stacks, as well as proximity of traffic to exposed populations. Both can cause small scale variation in pollutant concentrations, e.g., elevated concentrations of traffic-related air pollutant concentrations—and health impacts—near roadways (Batterman et al. 2015; Padró-Martínez et al. 2012; Patton et al. 2014) (Figure 3.2D), as shown in several cumulative impact studies (Pratt et al. 2015; Su et al. 2012, 2009). While exposures from point sources are mostly low (Table 3.1), they result in disproportionate health impacts because industry tends to cluster together (e.g., in southwest Detroit), because several facilities have short stacks that cause local "hot-spots," and because predominantly Hispanic/Latino residents live nearby (Figure A3.2). These results depend on the spatial layout, and possibly these factors are less aligned elsewhere, e.g., where industry is farther removed from urban area, though traffic impacts are common. Site-specific studies provide perhaps the only way to understand such health burden and equity implications. Because multiple source types are implicated as having substantial health burdens on different groups, strategies aimed at addressing environmental inequalities should target multiple source types to ensure that disadvantaged communities benefit from exposure reductions.

Subgroups shown to suffer disproportionate health impacts within the study area, which was selected given the potential for high exposures, include Hispanic/Latino residents and low-income residents. Typically, EJ and cumulative impact analyses use a single variable (persons of color) to assess inequality by race and ethnicity (e.g., Sadd et al. 2011). Across the larger metropolitan area (i.e., the tri-county metropolitan region or seven-county southeast Michigan region), aggregated variables may be sufficient to capture inequalities given the region's broad patterns of racial/ethnic segregation (e.g., Schulz et al. 2016); however, more targeted intra-urban analyses require further disaggregation by racial/ethnic minorities, otherwise, important inequalities may be missed. Characteristics used in an inequality assessment should reflect key demographic characteristics important to the specific area and should represent a reasonable fraction of the population to avoid artificially increasing inequality metrics. Addressing inequalities in exposure or risk for very small subgroups may not be feasible through public policy. Although establishing a uniform threshold for the size of the subgroup is impractical, chosen characteristics should start by identifying characteristics that highlight historical patterns of racial and ethnic segregation (Schulz et al. 2002) and socioeconomic status that influence heath disparities. Within the study area, and in particular within the city of Detroit (the largest city within the study area), there is less spatial variability in race (white vs. non-white) than ethnicity (Hispanic/Latino vs. non-Hispanic) or poverty status (Figure A3.2), and ethnicity and poverty status may better represent demographic gradients than race. Inequality analyses should also recognize that not all socially disadvantaged groups can be identified using available data. For example, in the city of Dearborn, 30% of the population identifies as Arab or Arab American (de la Cruz and Brittingham, 2003), many of whom experience high exposures to social stressors (Padela and Heisler, 2010; Samari, 2016). However, the US Census does not include data on Arab ethnicity, so this group cannot be examined with respect to inequality in health burden. In some cases, proxy characteristics, e.g., the percentage of the population that is foreign born, can be used instead (Figure A3.2).

The identification of disproportionately-impacted populations depends in part on which populations are included or excluded from the analysis. As discussed earlier, the study boundary for this analysis included the area expected to have the highest potential for health impacts, with some restrictions in scope due to dispersion modeling constraints. Focusing on the entire Detroit Metropolitan area, which includes Wayne, Oakland, and Macomb counties, would likely change the interpretation of the inequality metrics and demonstrate disproportionate impacts among more groups known to be socially disadvantaged, e.g., non-Hispanic Black/African American residents. As discussed earlier, the study area has higher proportions of persons of color (75.6%) compared to Wayne County as a whole (50.2%) (US Census Bureau, 2014). Compared with the study area, Oakland and Macomb counties have lower proportions of persons of color (26.0% and 17.9%, respectively) and persons living below the poverty level (10.4% and 12.8%, respectively) (US Census Bureau, 2014). Residents in these counties tend to be healthier than those living in Wayne County. For example, in 2014, Oakland and Macomb counties ranked 22nd and 39th in overall health, respectively, among counties in Michigan; Wayne County consistently ranks 82nd out of 82 counties in the state (RWJ Foundation, 2017). Due to their distance from major sources the presence of fewer heavily trafficked roads in Oakland and Macomb counties, we expect exposures, and thus health impacts, in these counties to be lower than the study area. Given the clustering of minority and low-income populations in the study area, the inequality metrics for exposures and health burdens are expected to be large for most if not all of the subgroups included in this study when examined within the context of the broader tri-county area.

Caution is needed when interpreting the results of the inequality assessment for the study area, as the result are only intended only to demonstrate inequality between census blocks within the study area. The results presented in this analysis should not be used to examine issues of inequality between residents of the study area and the broader southeast Michigan region. The absence of evidence of a disproportionate impact for certain groups, e.g., among census blocks with high proportions of Black or African American residents, should not be interpreted as evidence that these residents are not overburdened by their environmental exposures. A previous study of disparities across the tri-county region (using census tracts as the spatial unit of analysis) demonstrated residents in Detroit experience higher cumulative impacts from hazardous land uses, air pollutant exposures, and social vulnerabilities relative to other neighborhoods in the region (Schulz et al. 2016). The present analysis, limited in scope by the study boundary, is intended to help decisions makers identify those sections within the study area that are most heavily impacted, information which can be used to prioritize sections within a city for AQM activities. The results of this analysis or any intra-urban inequality assessment should be interpreted within the broader body of evidence on environmental justice issues in urban areas.

Exposures as a poor proxy for health risks in urban-scale inequality assessments

The finding from the inequality assessment that exposures alone are insufficient for representing health inequalities is important. Inequality metrics for health risks are driven, in addition to exposures, by the variability in baseline health risks, demographic variables, income, and other characteristics that influence vulnerability or susceptibility. This differs from many or possibly most earlier EJ and cumulative impact analyses that have relied on exposure indicators for a showing of disproportionate impacts, e.g., using ambient monitoring and dispersion modeling (e.g., Gray et al. 2013; Jones et al. 2014; Pope et al. 2016; Pratt et al. 2015; Prochaska et al. 2014; Su et al. 2012, 2009), and surrogates such as proximity to traffic or point sources (Batterman et al. 2014a; Brender et al. 2011). In addition, data from national datasets like the National Air Toxics Assessment (US EPA, 2015b) and air quality monitoring networks may not have the needed spatial resolution for local scale analyses of industry and traffic pollutants (Levy and Hanna, 2011; Matte et al. 2013). Factors that influence the necessary resolution, including the proximity of the source to exposed populations, source characteristics such as stack heights, meteorology, the vulnerability or susceptibility of exposed populations, and other factors (Fann et al. 2009), can become more important at smaller study scales.

The choice of which health impact metrics to use to assess inequality can be important for EJ and cumulative impact analyses. Prior inequality analyses of attributable health impacts have focused on the risk of specific health outcomes, e.g., premature mortality or hospitalizations, and on total risk rather than attributable risk (Fann et al. 2011; Levy et al. 2009, 2007). However, using a limited number of outcomes only captures a portion of the health burden due to pollutant exposures, and minor outcomes such as asthma exacerbations or restricted activity days that contribute greatly to overall health burdens (Table 3.2) should also be considered, especially if incidence rates vary spatially across the study area. DALYs provide a composite measure of health impacts that accounts for their severity and frequency and may be advantageous in inequality analyses. DALYs can help clarify which exposures and which sources are most important from a public health perspective. In some cumulative impact and EJ analyses, attributable risk may be more appropriate than total health risk (e.g., based on incidence rates). For example, transportation planners may be most interested in inequality in risk of mortality attributable to traffic emissions rather than total mortality risk. Although there is some uncertainty around the disability weights assigned to outcomes for DALYs (de Hollander et al. 1999; Haagsma et al. 2014), using DALYs to weight health impacts may be preferred over other cumulative impact approaches that assign uncertain weights to environmental and social determinants of health, e.g., pollutant exposures (Sadd et al. 2011).

Also, it is important to recognize that quantitative HIA methods capture some of the burden of disease, but cannot account for other health risks for which reliable CR coefficients are not available (O'Connell and Hurley, 2009) or other important dimensions of environmental justice, e.g., the perception that communities are more polluted (Brody et al. 2004). The air pollution-related outcomes for which HIFs are available are limited, and other metrics of exposure and health burden may still be important considerations. For example, proximity to environmental hazards has other important risks beyond exposure to ambient air pollutants, e.g., living near industrial facilities may negatively impact mental health (Downey and Willigen, 2005), and noise pollution from roadways may contribute to sleep disturbance and cardiovascular disease (Basner et al. 2014). Health impact and inequality analyses designed for specific public health decisions should include quantitative and qualitative descriptions of the health impacts of air pollutants. An explicit weighting system could be used to combine effects from descriptive and quantitative assessments.

Using urban-scale HIAs incorporating inequality metrics in AQM decision making

Information about which sources and pollutants contribute most to environmental inequalities is important for public health priority setting, particularly at the local level where resources might be constrained. Quantitative estimates of health impacts may be particularly useful for decision makers, especially when compared to established health targets or standards (Bhatia and Seto, 2011; Fehr et al. 2012). The findings that mobile source emissions have disproportionate impacts on low income residents could be used to focus urban greening projects in areas with both high exposures and high percentages of low-income residents, thus helping to alleviate health burdens and disparities. Because increased access to green space can increase property values and make urban neighborhoods more attractive, programs to increase green space in low-income neighborhoods should be coupled with programs to support existing communities to avoid potential issues of gentrification and displacement (Wolch et al. 2014). Likewise, knowing that point and mobile sources of $PM_{2.5}$ have a disproportionate impact in southwest Detroit (Figure 3.2), particularly among the Hispanic and Latino populations that live in the area (Table 3.4), could be used to prioritize schools in southwest Detroit for installation of filters to reduce exposures. Despite the potential benefits of using inequality metrics to inform environmental decision making, we do not necessarily advocate performing equity analyses by pollutant source for all public health decisions because health impacts result from the totality of exposure. The previous examples of increasing green space and using filters in schools pertain to reducing exposures to specific air pollutants. Any reduction in exposures can lead to some health benefits, so identifying groups that are disproportionately impacted allows AQM activities to be targeted to simultaneously reduce health impacts and health disparities.

For decisions that will potentially increase emissions or exposures for some subpopulations, however, source-and pollutant-specific assessments are not appropriate. Decisions related to permitting or facility siting, for example, should include health and cumulative impact assessments that consider only total exposures to a number of social and environmental hazards to avoid increasing cumulative burdens for any segment of the population.

Some additional considerations for urban-scale HIAs follow from the results of this study. First, exposure assessments should be based on the spatially- and temporally-resolved data that best reflect variability over the urban area. For example, several pollutants demonstrate high degrees of spatial and temporal variability that can lead to greater exposures for subsections of the study area (Figure 3.3A, Figure 3.3B, and Figure A3.4), and assessing exposures at larger spatial units (e.g., ZIP codes) smooths exposure gradients across the study area (Table 3.3). Dispersion or land use regression models, though time- and resource-intensive, may provide a reasonable option to estimate exposures with the necessary spatial resolution (Batterman et al. 2015, 2014a; Bertazzon et al. 2015; Hoek et al. 2008; Jerrett et al. 2005). Partnering with state or local agencies or academic partners could be helpful in building capacity to model pollutant exposures at the local level. In general, studies that utilize spatially-resolved estimates of exposure and health risks are preferred over less refined exposure assessments, and studies that incorporate health burdens in the assessment are preferred overall.

Second, the study scale and spatial resolution should be appropriate for the policy context. The sensitivity of the inequality determinations to study boundaries and spatial scale, while not surprising, emphasizes the need to structure analyses based on potential impacts (Harper et al. 2013) and the policy or intervention context. For this burden of disease assessment, the study boundaries are based on the potential for exposures and health impacts, on the ability to model these exposures and health impacts at a sufficiently fine spatial scale, and on the decision-making authority of local governments. As discussed above, the results of this study could be used by decision makers with authority within the study area to prioritize AQM activities in their respective cities. The same study boundaries may not be appropriate for all intervention analyses. For assessments of specific AQM policies or programs, the selection of study boundaries needs to be deliberate and explicitly stated. For example, a decision about routing traffic, which could be influenced by a local government, requires a finely grained assessment at the intra-urban scale where impacts are expected to be localized to the area around the roadways; regional-scale decisions about how to reduce O_3 concentrations, which involve multiple actors and require coordination across governmental agencies, would use less spatially resolved data and a larger study area. The study scale and study resolution in particular will depend on the availability of input health and exposure data. Sensitivity analyses should be used to explore implications and the robustness of selected boundary and spatial unit.

Third the characteristics used to identify inequalities might be tailored to the specific study area. Every urban area will have a unique spatial distribution of populations, and the selection of appropriate proxies for vulnerability will vary. Variables used to examine inequality should be selected after reviewing historical and current population trends. For example, this study area contains a large Arab and Arab American population in Dearborn, MI that is not well represented using census data. However, there are large proportions of residents that are foreign born in Dearborn (Figure A3.2). Though not all of these foreign-born residents will be Arab or Arab American, this variable may be a reasonable proxy for the Arab population within the study area.

Lastly, HIAs using inequality metrics in a decision-making context should consider the entire policy context, not just metrics of health and inequality. It is important to note that health and inequality metrics alone do not identify optimal strategies or prioritize pollutants or source categories. Similarly, the inequality metrics provide relative measures, and there are no thresholds or standards for inequality or equality. For example, this analysis suggests $PM_{2.5}$ from regional sources has the highest public health burden but the lowest degree of inequality, while point source emissions impose a relatively low burden but significant degree of inequality. Whether strategies should focus on achieving the greatest overall reductions in health burden or health inequality is a matter of policy. In addition to health and equity, decision makers will need to consider legal, economic, and political ramifications of public policy decisions, as well as community preferences for air quality management strategies.

Uncertainty in the quantitative health impact assessments

Uncertainties in quantitative HIA methods and inequality assessments influence the interpretation of results. The exposure assessment omits time-activity data, which may underestimate exposure when people spend substantial time in areas with higher concentrations than their residences (Baccini et al. 2015; Tchepel and Dias, 2011). Uncertainty around the CR coefficient has the largest influence on health impact estimates (Chart-asa and Gibson, 2015). (This study presents only the mean, i.e. expected, health impacts.) Other sources of uncertainty include: the appropriateness and generalizability of the CR coefficient; whether the form of the HIF is appropriate; whether the exposure-outcome relationships are reasonable; the downscaling of census block group and ZIP code level demographic and baseline health rate data to the census block scale; the disability weights and duration variables used in the calculation of DALYs; uncertainties in the modeled estimates of ambient pollutant concentrations; and, potential double-counting of impacts when estimating attributable burdens from multiple pollutants (Briggs et al. 2009; Fuentes, 2009; Haagsma et al. 2014; Levy, 2003; Mesa-Frias et al. 2013). Despite these and other uncertainties, the use of HIAs and inequality metrics offers decision-makers an objective approach to indicate the nature, magnitude, and distribution of health impacts.

Conclusions

This study has estimated the health burden attributable to exposures of $PM_{2.5}$, O_3, NO_2 and SO_2 in the Detroit area, identified the role of point, mobile, and area sources, and examined inequality of exposures and attributable health risks for population subgroups defined by demographics or socioeconomic characteristics. Exposure to ambient pollutants imposes a substantial health burden on Detroit residences, mostly due to $PM_{2.5}$ and O_3 exposures, most of which arises from regional sources. While local point and mobile sources impose lower health impacts overall, these sources contribute most to the inequality in the health burden experienced by socially disadvantaged populations. The methods presented can be used to inform decision making aimed at reducing environmental health burdens and inequalities, including identifying culpable sources and designing air quality management strategies to improve public health.

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Table 3.1. Summary statistics of daily concentrations of $PM_{2.5}$ and DPM (daily mean, μg/m^3), O_3 (daily 8-hr max, ppb), SO_2 (daily mean, ppb), and NO_2 (daily mean, ppb). Contributions from regional, point, mobile and area sources are separated. Estimated at the census block level.

Pollutant	Source	Mean (SD)	Min	25th	Median	75th	95th	Max
$PM_{2.5}$ (μg/m^3)	Regional	8.3 (4.5)	1.5	5.2	6.8	11.3	14.5	29.5
	Point	0.5 (0.9)	0.0	0.1	0.3	0.6	1.4	75.7
	Mobile	0.6 (0.5)	0.0	0.3	0.4	0.7	1.6	12.7
	Area	1.8 (2.8)	0.0	0.2	1.0	2.2	6.3	29.4
	Total	10.7 (5.4)	2.0	6.5	9.9	13.5	19.7	82.4
DPM (μg/m^3)	Mobile	0.5 (0.6)	0.0	0.2	0.4	0.6	1.5	12.3
O_3 (ppb)	Regional	38.3 (13.7)	6.8	28.2	36.4	46.9	63.4	103.8
SO_2 (ppb)	Point	1.1 (1.4)	0.0	0.1	0.5	1.6	4.0	19.4
NO_2 (ppb)	Regional	10.9 (5.1)	2.6	7.7	9.7	12.9	23.0	30.2
	Point	1.4 (1.1)	0.0	0.5	1.1	1.9	3.5	17.0
	Mobile	10.2 (9.0)	0.0	4.3	7.6	13.0	27.1	191.9
	Area	1.7 (3.0)	0.0	0.0	0.0	2.6	8.8	17.2
	Total	23.5 (10.5)	5.8	17.3	21.9	26.0	43.1	214.2

Table 3.2. Estimated annual incidence for the health outcomes of interest and total annual burden of disease as attributable cases, disability-adjusted life years, and monetized impacts attributable to $PM_{2.5}$, O_3, SO_2, and NO_2 from regional, point, mobile, and area sources. Rounded to two significant figures.

		Attributable Impacts								
			Exposure source				% of attributable burden due to each pollutant			
Outcome (age group)	Estimated annual incidence[1]	Total (%[2])	Regional	Point	Mobile	Area	$PM_{2.5}$	O_3	SO_2	NO_2
Mortality (cases)										
All-cause (>29)	9,400	520 (5.5)	420	24	27	84	100	0	0	0
Non-accidental (>29)	8,800	140 (1.5)	140	0	0	0	0	100	0	0
Infant (<1)	200	6 (4.0)	5	0	0	1	100	0	0	0
Hospitalizations (cases)										
Asthma (<65)	3,200	210 (6.7)	140	17	46	16	51	0	3	46
COPD (>65)	1,900	419 (22.4)	330	48	40	12	5	62	10	23
CVD (>65)	9,800	160 (1.6)	130	7	8	8	100	0	0	0
Pneumonia (>65)	1,500	250 (17.3)	240	3	3	3	23	77	0	0
Non-fatal MI (>17)	2,600	60 (2.3)	48	3	3	3	100	0	0	0
Asthma outcomes (cases)										
Asthma ED visit (<18)	9,000	3,300 (36.7)	2600	160	450	120	15	51	2	31
Day w/ cough (6 – 14)	1,700,000	210,000 (12.5)	170,000	10,000	11,000	9,500	100	0	0	0
Day w/ wheeze (6 – 14)	1,100,000	17,000 (1.6)	13,000	780	820	740	100	0	0	0
Day w/ SoB (6 – 14)	1,000,000	21,000 (2.1)	17,000	1,000	1,000	940	100	0	0	0
2+ symptoms (6 – 14)	2,000,000	180,000 (8.6)	110,000	12,000	45,000	9,600	0	34	3	64
Restricted days										
MRAD (18 – 64)	4,600,000	760,000 (16.7)	700,000	16,000	18,000	18,000	44	56	0	0
WLD (18 – 64)	1,300,000	59,000 (4.7)	47,000	2,800	3,000	3,100	100	0	0	0
MSD (6 – 14)	2,700,000	570,000 (21.3)	570,000	0	0	0	0	100	0	0
Total DALYs (years)		10,000	8,100	470	560	1,600	97	1	0.06	1.3
Monetized impact ($million)		6,600	5,500	240	280	830	78	21	0.03	0.5

[1] Estimated annual incidence rates based on block group population and ZIP code level incidence rates

[2] Percentage of the estimated annual incidence attributable to all pollutant exposures

Abbreviations: COPD: Chronic obstructive pulmonary disease; CVD: cardiovascular disease; DALYs: disability-adjusted life years; ED: emergency department; MI: myocardial infarction; MRAD: minor restricted activity day; MSD: missed school day; SoB: shortness of breath; WLD: work loss day

Table 3.3. Atkinson index (AI)[1] for annual average pollutant exposure and annual health impact (as risk of a DALY per year) attributable to individual pollutants for the full analysis, and for sensitivity analyses of spatial resolution and region. Percentages (in parentheses) show change from "all blocks." Negative percentages indicate increases in AI.

		Annual average exposures[2]			Annual health impact risk		
Pollutant	Source	All blocks	ZIP codes	NA area[3]	All blocks	ZIP codes	NA area[3]
$PM_{2.5}$	Regional[4]	—	—	—	0.041	0.022 (46)	0.038 (7)
	Point	0.101	0.139 (-37)	0.107 (-5)	0.126	0.154 (-22)	0.157 (-25)
	Mobile	0.079	0.057 (29)	0.128 (-61)	0.126	0.084 (34)	0.153 (-21)
	Area	0.070	0.019 (73)	0.082 (-18)	0.113	0.045 (60)	0.111 (1)
	Total	0.003	0.001 (62)	0.003 (-13)	0.045	0.023 (49)	0.041 (8)
O_3	Regional[4]	—	—	—	0.040	0.023 (43)	0.038 (4)
SO_2	Point	0.064	0.055 (13)	0.043 (33)	0.155	0.075 (51)	0.116 (25)
NO_2	Regional[4]	—	—	—	0.133	0.038 (72)	0.096 (28)
	Point	0.034	0.027 (23)	0.042 (-21)	0.159	0.057 (64)	0.140 (12)
	Mobile	0.084	0.055 (34)	0.126 (-50)	0.191	0.072 (62)	0.203 (-7)
	Area	0.130	0.101 (22)	0.163 (-26)	0.245	0.141 (43)	0.225 (8)
	Total	0.009	0.011 (-18)	0.012 (-25)	0.137	0.045 (67)	0.104 (24)

[1] Inequality aversion parameter set to 0.75

[2] $PM_{2.5}$, SO_2, and NO_2 are reported as the average of daily mean concentrations and O_3 is reported as the average of daily 8-hr maximum concentrations.

[3] Subset of study area census blocks that are within the SO_2 non-attainment area.

[4] Regional exposures are omitted from the Atkinson index because all spatial units are assigned the same concentration.

Abbreviations: NA: Non-attainment

Table 3.4. Concentration index values (× 100) for annual risk of a DALY per year attributable to individual pollutants for the full analysis, and for sensitivity analyses of spatial resolution and region. Negative values indicate disproportionately high health burdens in socially disadvantaged spatial units. Percentages (in parentheses) show change from "all blocks."

		Concentration index (× 100)						
Pollutant	Source	% non-white	% Latino	% less than HS	Median income	% HH in poverty	% POC	% FB
All census blocks								
$PM_{2.5}$	Regional	-6.7	3.0	-1.0	-4.1	-1.2	-6.4	6.5
	Point	5.4	-11.7	-8.2	-3.1	-0.2	3.8	-5.7
	Mobile	-6.6	0.8	-4.6	-8.7	-5.5	-6.8	6.1
	Area	-7.6	4.0	0.4	-4.5	-1.8	-7.0	7.9
	Total	-6.3	2.4	-1.3	-4.4	-1.5	-6.1	6.1
O_3	Regional	-6.2	3.0	-0.6	-3.4	-0.5	-5.9	6.1
SO_2	Point	8.1	-13.3	-11.1	-3.3	-6.9	6.0	-12.4
NO_2	Regional	1.3	-2.1	-3.6	-0.8	-5.0	0.7	-4.3
	Point	5.8	-9.3	-8.9	-2.8	-7.0	4.1	-10.1
	Mobile	-1.0	-3.4	-7.2	-5.0	-8.4	-2.3	-2.6
	Area	3.6	-0.6	2.8	4.4	0.2	4.1	-4.7
	Total	0.8	-3.0	-4.9	-2.3	-6.1	-0.1	-3.9
ZIP codes								
$PM_{2.5}$	Regional	-8 (-19)	4.1 (-35)	-0.5 (49)	-8.2 (-101)	-4.3 (-269)	-8.2 (-27)	7.8 (-21)
	Point	8.5 (-58)	-23.7 (-102)	-12.9 (-57)	-6.1 (-95)	-6.1 (-2973)	2.2 (41)	-8.2 (-44)
	Mobile	-4.4 (33)	-0.8 (193)	-1.4 (70)	-18.6 (-114)	-13.5 (-143)	-6.1 (11)	1.1 (81)
	Area	-9.2 (-22)	8.7 (-121)	1 (-139)	-8.1 (-81)	-4.8 (-165)	-8.6 (-23)	10.1 (-28)
	Total	-7.7 (-21)	3 (-25)	-0.6 (57)	-8.1 (-85)	-3.9 (-166)	-8 (-32)	7.4 (-21)
O_3	Regional	-8.2 (-32)	4.6 (-52)	-0.8 (-35)	-8.4 (-149)	-4.2 (-823)	-8.1 (-39)	7.5 (-23)
SO_2	Point	11.1 (-37)	-15.2 (-15)	-18.7 (-68)	-3.2 (4)	-7.2 (-4)	8.3 (-40)	-12.1 (3)
NO_2	Regional	1.5 (-16)	-0.9 (58)	-6.5 (-84)	1.6 (296)	-2.2 (56)	1.1 (-59)	-3 (30)
	Point	8.5 (-46)	-11 (-19)	-15.1 (-69)	-1.1 (59)	-5.7 (18)	6.3 (-53)	-10.1 (0)
	Mobile	1.9 (295)	-2.7 (20)	-9.1 (-27)	-7.8 (-55)	-10.3 (-24)	0.2 (107)	-6.5 (-154)
	Area	-3.9 (207)	8.4 (1421)	4.8 (-72)	7.5 (-69)	4.8 (-2110)	-2.4 (158)	9.4 (301)
	Total	3.3 (-316)	-4.4 (-47)	-10.1 (-106)	0.1 (105)	-4.2 (32)	2.1 (1867)	-6.3 (-60)
Census blocks in the SO_2 non-attainment area								
$PM_{2.5}$	Regional	-3.8 (43)	6.1 (-102)	5.8 (702)	0.6 (115)	3 (362)	-1.3 (79)	7.1 (-10)
	Point	-11.3 (310)	2.7 (123)	-3.2 (61)	-8.9 (-184)	-5.5 (-2663)	-11.6 (406)	6.2 (208)
	Mobile	-9.2 (-40)	-0.9 (205)	-0.1 (98)	-6 (31)	-4.1 (26)	-9.3 (-37)	1.8 (71)
	Area	-0.4 (95)	7.8 (-98)	10.9 (-2598)	5.7 (227)	6 (430)	3.3 (147)	7.7 (2)
	Total	-4.4 (31)	5.4 (-125)	5 (486)	-0.1 (97)	2.1 (241)	-2.2 (64)	6.6 (-8)
O_3	Regional	-3.3 (46)	6.5 (-117)	6.5 (1168)	1.5 (143)	3.9 (965)	-0.8 (87)	7.1 (-18)
SO_2	Point	-6.1 (175)	-11.2 (16)	-12.6 (-13)	-8.7 (-160)	-10.9 (-58)	-9.2 (254)	-10.1 (19)
NO_2	Regional	-0.6 (148)	-8.6 (-319)	-8.4 (-137)	-3.9 (-394)	-6.1 (-24)	-3.5 (609)	-9 (-109)
	Point	-5.9 (202)	-12 (-29)	-13.4 (-49)	-9.7 (-252)	-11.9 (-71)	-9.7 (334)	-11.2 (-11)
	Mobile	-5.7 (-469)	-16.8 (-392)	-15.3 (-115)	-10.2 (-103)	-12.5 (-50)	-11.1 (-375)	-15 (-488)
	Area	6.5 (-82)	7.2 (1225)	8.1 (-189)	7.6 (-73)	6.4 (-2835)	9.2 (-125)	7 (250)
	Total	-2.6 (429)	-11.3 (-279)	-10.6 (-117)	-6.1 (-170)	-8.4 (-37)	-6.2 (-5256)	-10.6 (-171)

Figure 3.1. Map showing the full study area boundary and the study boundaries used in the sensitivity analyses. Black dots show the location of ambient air quality monitors in the area. The shaded area has been classified as non-attainment with the SO_2 NAAQS.

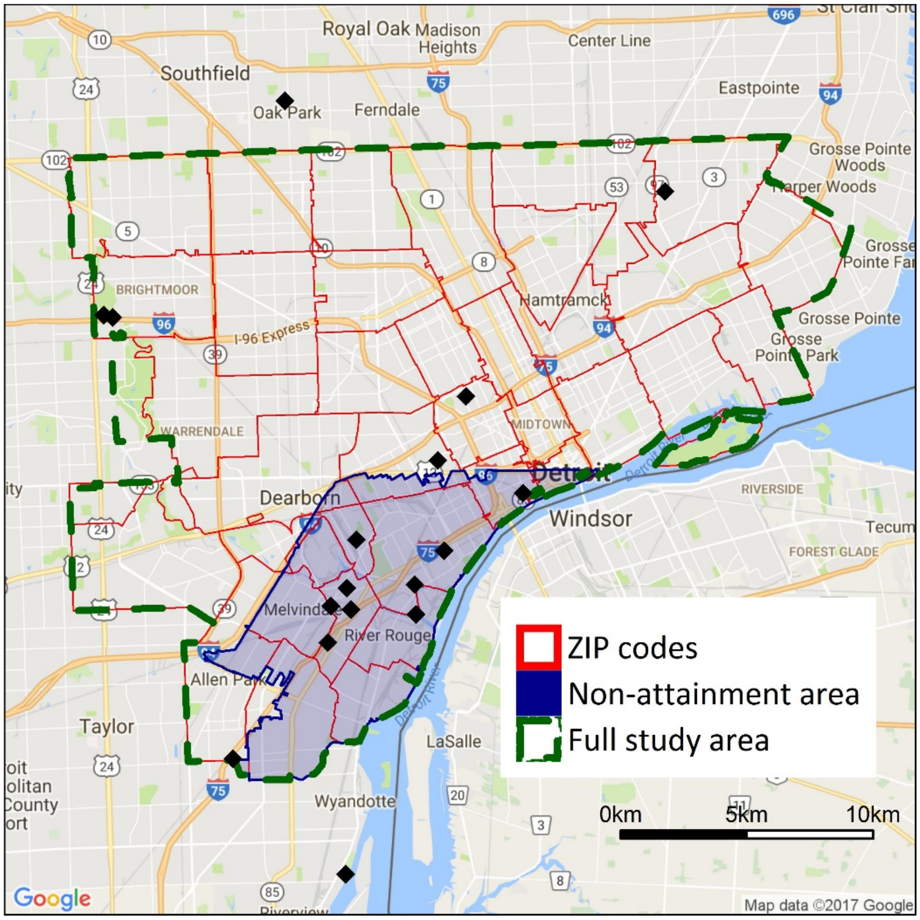


Figure 3.2. Maps showing the annual health burden as DALYs per 10,000 persons per year attributable to exposures from all sources (A), and exposures from regional (B), point (C), mobile (D), and area sources (E).

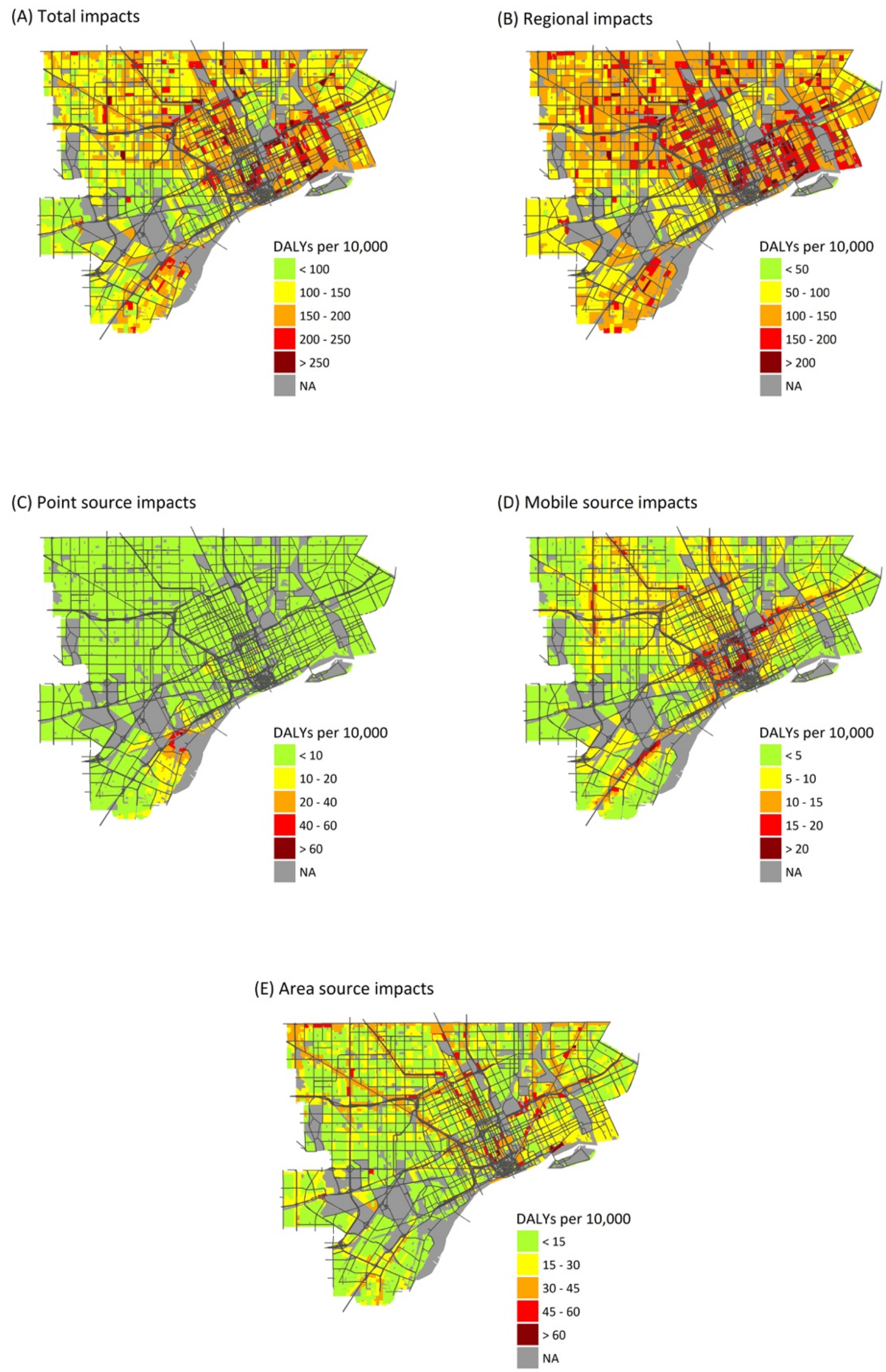
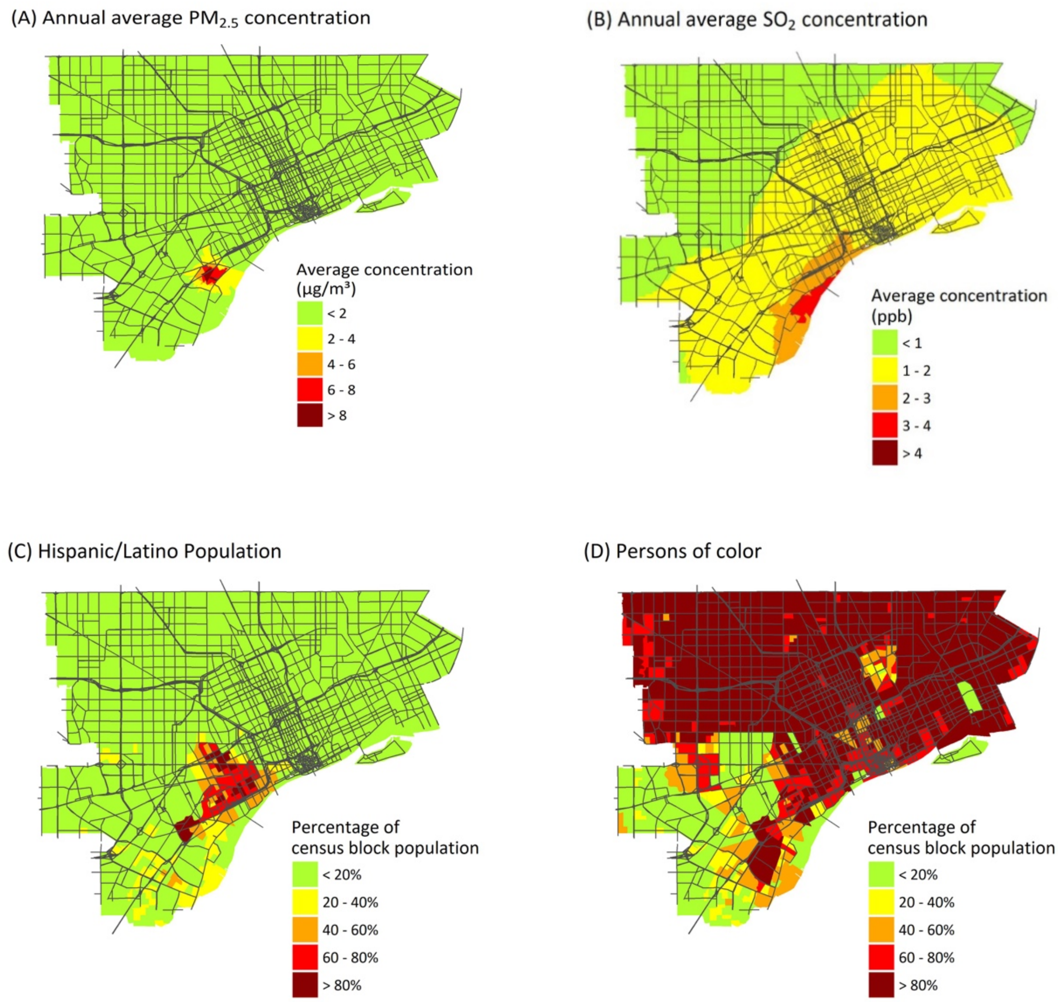


Figure 3.3. Annual average ambient concentrations from point sources of $PM_{2.5}$ (A) and SO_2 (B); Percentage of the population identifying as Hispanic or Latino (C), or as persons of color (D; excludes non-Hispanic whites).



Appendix A3

SUPPLEMENTAL MATERIALS FOR CHAPTER 3

Supplemental Methods

The following section provides additional details on the methods used in this study.

Quantitative health impact functions

Each HIF predicts the number of attributable cases (Y) and requires four inputs: 1) a baseline incidence rate for the health outcome of interest (y_0, cases per person per day); 2) a concentration-response relating an exposure concentration to a change in health outcome risk (β, risk per unit exposure); 3) an estimate of the exposure concentration (x, units of concentration, e.g., ppb or $\mu g/m^3$); and 4) an estimate of the exposed population (P, persons). The HIF is derived from the expression of relative risk, and the form of the equation depends on the model used to estimate the CR coefficient. This study relies on two forms of the HIF: a log-linear form (eq. A3.1) and a logistic form (eq. A3.2).

$$Y = y_0 \left(1 - e^{-\beta x}\right) P \tag{A3.1}$$

$$Y = y_0 \left(1 - 1 / \{ [1 - y_0]\, e^{\beta x} + y_0 \}\right) P \tag{A3.2}$$

We apply the HIF for each pollutant-outcome pair to each census block *u* using block-specific estimates of baseline rates ($y_{0,u}$), exposure concentrations (x_u), and exposed populations (p_u) to estimate the number of block-specific attributable impacts (Y_u). The total number of attributable health impacts for each pollutant-outcome pair across the entire study area is given by $\sum_{u=1}^{n} Y_u$, where *n* is the total number of census blocks in the study area.

The health outcomes included in the HIFs were chosen based on the strength of causal association as determined by the US EPA in their Integrated Science Assessments (ISAs; US EPA, 2013, 2009a, 2009b, 2008). Baseline incidence rates used in the HIFs come from multiple sources and are available at various spatial scales. Rates are downscaled to the census block level. Mortality rates at the ZIP code level (2009-2013) are calculated using geocoded mortality data made available by the Michigan Department of Health and Human Services (MDHHS) and 5-year age-stratified population estimates from the 2013 ACS survey (US Census Bureau, 2015). Hospitalization rates at the ZIP code level (2009-2013) are based on hospitalization data for Wayne County hospitals and 2013 ACS survey population estimates. Rates for ED visits for asthma are available at the ZIP code level for Detroit and the county level outside of Detroit (DeGuire et al. 2016; MDHHS, 2016). Rates for Asthma related respiratory symptom day rates are taken from a cohort study of children with asthma in Detroit (Batterman et al. manuscript in preparation). Rates for other health outcomes, including non-fatal heart attacks, work and school absence days, and minor-restricted activity days are not available for the study area, so national rates used in HIA conducted by the US EPA are substituted (US EPA, 2015). Maps showing the ZIP-code level baseline health rates are included below.

The CRs used in this study have been taken from studies identified by the US EPA for inclusion in Integrated Science Assessments for O_3, $PM_{2.5}$, SO_2, and NO_2 (US Environmental Protection Agency [US EPA], 2013, 2009a, 2009b, 2008). The BenMAP User's Manual (US EPA, 2015) and the epidemiological literature were also reviewed to identify other potential studies for inclusion. In addition to the studies summarized by the ISAs, effect estimates from studies conducted in Detroit were also considered, as local studies may better reflect the underlying risk than studies conducted elsewhere, but can be subject to limitations based on statistical power or study design (Hubbell et al. 2009). CR coefficients apply to specific age groups based on the study populations of the original epidemiology studies from which they are drawn. The CR coefficients for each of the pollutant-outcome pairs are listed in Table A3.1.

The HIA methods described here use three metrics to estimate health burden: the number of incident cases of mortality or morbidity attributable to pollutant exposure (attributable cases), disability-adjusted life years (DALYs), and monetized impacts. DALYs and monetized impacts are derived from the number of attributable cases. A DALY is the sum of years of life lost (due to premature mortality) and years lived with disability (due to morbidity), and calculations require a disability-weight (DW) and duration (D) for each outcome (Murray, 1994). Monetized values are typically assigned to mortalities based on the value of a statistical life (VSL) and to morbidities based on the cost of illness (COI) or willingness to pay (WTP) estimates (US EPA, 2010). In order to monetize the health impacts, monetary values from the Regulatory Impact Analysis for the most recent particulate matter standard in the US are used (US EPA, 2012).

Monetized values are reported in 2010 dollars projected to a 2020 income level. DW, duration and monetized values for each of the health outcomes in the HIA are listed in Table A3.2.

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Supplemental Tables

Table A3.1. Pollutants, health outcomes, age groups, and concentration-response coefficients used in the health impact functions

Pollutant	Health Outcome	Age group	CR	Form	Reference
O_3	Non-accidental mortality	30+	0.00041	log-linear	Smith et al. 2009
	ED visit for asthma	0-17	0.01044	log-linear	Mar and Koenig, 2009
	Asthma symptom day (one or more symptoms)	6-14	0.00194	logistic	Schildcrout et al. 2006
	Pneumonia hospitalization	65+	0.00521	log-linear	Schwartz, 1994
	COPD hospitalization	65+	0.00549	log-linear	Schwartz, 1994
	Missed school day	6-14	0.00755	log-linear	Gilliland et al. 2001
	Minor restricted activity day	18-64	0.00260	log-linear	Ostro and Rothschild, 1989
$PM_{2.5}$	All-cause mortality	30+	0.00545	Log-linear	Krewski, 2009
	Infant mortality	0-1	0.00392	logistic	Woodruff et al. 1997
	Asthma hospitalization	0-64	0.00332	log-linear	Sheppard, 2003
	COPD hospitalization	65+	0.00117	log-linear	Ito, 2003
	CVD hospitalization	65+	0.00158	log-linear	Moolgavkar, 2003
	Pneumonia hospitalization	65+	0.00398	log-linear	Ito, 2003
	Non-fatal heart attack	18+	0.00222	logistic	Zanobetti et al. 2008
	ED visit for asthma	0-17	0.00560	log-linear	Mar et al. 2010
	Asthma symptom day (cough)	6-14	0.01906	logistic	Mar et al. 2004
	Asthma symptom day (shortness of breath)	6-14	0.00256	logistic	Ostro et al. 2001
	Asthma symptom day (wheeze)	6-14	0.00194	logistic	Ostro et al. 2001
	Minor restricted activity day	18-64	0.00741	log-linear	Ostro and Rothschild, 1989
	Work loss day	18-64	0.00460	log-linear	Ostro, 1987
SO_2	Asthma hospitalization	0-64	0.00203	log-linear	Sheppard, 2003
	COPD hospitalization	65+	0.02081	log-linear	Yang et al. 2005
	ED visit for asthma	0-17	0.00853	log-linear	Ito et al. 2007
	ED visit for asthma (Detroit CR)	0-17	0.00976	log-linear	Li et al. 2011
	Asthma symptom day (one or more symptoms)	6-14	0.00392	logistic	Schildcrout et al. 2006
	Asthma symptom day (one or more symptoms, Detroit CR)	6-14	0.01695	logistic	Batterman et al. in prep
NO_2	Asthma hospitalization	0-64	0.00140	log-linear	Linn et al. 2000
	COPD hospitalization	65+	0.0024	log-linear	Moolgavkar, 2003
	ED visit for asthma	0-17	0.00546	log-linear	Ito et al. 2007
	Asthma symptom day (one or more symptoms)	6-14	0.00431	logistic	Schildcrout et al. 2006

Table A3.2. Disability weights, duration, and monetary values used to estimate disability-adjusted life years and monetized impacts

Outcome	Age	DW (--)	D (years)	V ($)	DW Source	D Source	V Source
Mortality							
All-cause	30-34	1	49.327	9600000		MDHHS, 2015	US EPA, 2012
All-cause	35-30	1	44.645	9600000		MDHHS, 2015	US EPA, 2012
All-cause	40-44	1	39.978	9600000		MDHHS, 2015	US EPA, 2012
All-cause	45-49	1	35.406	9600000		MDHHS, 2015	US EPA, 2012
All-cause	50-54	1	30.962	9600000		MDHHS, 2015	US EPA, 2012
All-cause	55-59	1	26.726	9600000		MDHHS, 2015	US EPA, 2012
All-cause	60-64	1	22.653	9600000		MDHHS, 2015	US EPA, 2012
All-cause	65-69	1	18.745	9600000		MDHHS, 2015	US EPA, 2012
All-cause	70-74	1	15.056	9600000		MDHHS, 2015	US EPA, 2012
All-cause	75-79	1	11.68	9600000		MDHHS, 2015	US EPA, 2012
All-cause	80-84	1	8.627	9600000		MDHHS, 2015	US EPA, 2012
All-cause	85+	1	5.9	9600000		MDHHS, 2015	US EPA, 2012
Infant	0-1	1	77.923	9600000		MDHHS, 2015	US EPA, 2012
Hospitalizations							
Asthma	0-64	0.64	0.009	16000	de Hollander 1999	CDC, 2012	US EPA, 2012
COPD	65+	0.64	0.012	36000	de Hollander 1999	CDC, 2012	US EPA, 2012
CVD	65+	0.71	0.0126	41000	de Hollander 1999	CDC, 2012	US EPA, 2012
Pneumonia	65+	0.64	0.014	36000	de Hollander 1999	CDC, 2012	US EPA, 2012
Non-fatal MI	18+	0.42	0.015	143000	de Hollander 1999	CDC, 2012	US EPA, 2012
Asthma outcomes							
ED Visit	0-17	0.51	0.0027	430	de Hollander 1999		US EPA, 2012
Cough		0.22	0.005	58	de Hollander 1999		US EPA, 2012
SoB		0.22	0.005	58	de Hollander 1999		US EPA, 2012
Wheeze		0.22	0.005	58	de Hollander 1999		US EPA, 2012
One or more		0.22	0.005	58	de Hollander 1999		US EPA, 2012
Restricted activity days							
MRAD		0.092	0.0027	68	Murray, 1994	Ostro, 1987	US EPA, 2012
WLD		0.092	0.0027	150	Murray ,1994		US EPA, 2012
SLD		0.092	0.0027	98			US EPA, 2016

Abbreviations: COPD: chronic obstructive pulmonary disease; CVD: cardiovascular disease; D: duration; DW: disability weight; ED: emergency department; MI: myocardial infarction; MRAD: minor restricted activity day; SLD: school loss day (school absence); WLD: work loss day

Table A3.3. Concentration index values (× 100) for annual average exposure concentration attributable to individual ambient air pollutants for the full analysis and the two sensitivity analyses. Percentages in parentheses are the percent difference between the sensitivity analysis values and the "all blocks" analysis.

		Concentration index (× 100)						
Pollutant	Source	% non-white	% Latino	% less than HS	Median income	% HH in poverty	% POC	% FB
				All census blocks				
$PM_{2.5}$	Regional	—	—	—	—	—	—	—
	Point	12.9	-15.4	-8.9	0.8	0.7	10.9	-13.2
	Mobile	-0.5	-2.6	-4.0	-4.4	-4.0	-1.1	0.0
	Area	-1.1	0.9	1.7	-0.2	-0.2	-0.8	1.7
	Total	0.4	-0.7	-0.4	-0.3	-0.2	0.3	-0.4
O_3	Regional	—	—	—	—	—	—	—
SO_2	Point	6.8	-10.6	-7.0	-2.7	-2.9	5.7	-7.8
NO_2	Regional	—	—	—	—	—	—	—
	Point	4.3	-6.6	-4.9	-2.0	-2.3	3.5	-5.2
	Mobile	-2.0	-1.0	-3.6	-4.5	-4.1	-2.6	1.4
	Area	3.4	0.6	6.4	5.9	6.1	4.2	-0.8
	Total	-0.3	-0.8	-1.3	-1.6	-1.4	-0.5	0.2
				ZIP codes				
$PM_{2.5}$	Regional	—	—	—	—	—	—	—
	Point	0.139 (-37)	16 (-23)	-27 (-76)	-14.8 (-66)	1 (-35)	-2.7 (508)	9.7 (11)
	Mobile	0.057 (29)	2.7 (681)	-4.5 (-71)	-2.2 (46)	-9.9 (-126)	-8.4 (-110)	1.2 (208)
	Area	0.019 (73)	-1.8 (-61)	4.9 (-425)	1.6 (10)	-0.1 (55)	-0.8 (-301)	-0.9 (-13)
	Total	0.001 (62)	0.5 (-17)	-1.2 (-72)	0.1 (116)	0.2 (185)	0.5 (295)	0.2 (26)
O_3	Regional	—	—	—	—	—	—	—
SO_2	Point	0.055 (13)	9.5 (-40)	-13.7 (-29)	-10.7 (-53)	-4.4 (-60)	-4.8 (-64)	7.7 (-36)
NO_2	Regional	—	—	—	—	—	—	—
	Point	0.027 (23)	6.9 (-59)	-9.8 (-48)	-7.5 (-54)	-2.6 (-31)	-3.4 (-48)	5.4 (-52)
	Mobile	0.055 (34)	1.1 (152)	-2.5 (-163)	-1.4 (60)	-9.9 (-120)	-8.5 (-109)	-0.1 (95)
	Area	0.101 (22)	-4.8 (239)	8.4 (-1278)	7.9 (-24)	4.2 (28)	4.7 (23)	-3.5 (183)
	Total	0.011 (-18)	1.6 (578)	-3.1 (-291)	-2.1 (-56)	-0.6 (60)	-0.9 (36)	1.2 (315)
				Census blocks in the SO_2 non-attainment area				
$PM_{2.5}$	Regional	—	—	—	—	—	—	—
	Point	0.107 (-5)	-6.9 (153)	-3.7 (76)	-9.5 (-7)	-9.5 (1328)	-9.1 (1482)	-9.4 (186)
	Mobile	0.128 (-61)	-4.7 (-914)	-7.5 (-186)	-6.4 (-58)	-6 (-37)	-6.3 (-57)	-7.3 (-556)
	Area	0.082 (-18)	3.7 (429)	2.2 (-134)	5.8 (-233)	5.2 (3341)	4 (2091)	5 (719)
	Total	0.003 (-13)	-0.5 (217)	-0.7 (-2)	-0.8 (-110)	-0.7 (-178)	-0.9 (-242)	-0.7 (339)
O_3	Regional	—	—	—	—	—	—	—
SO_2	Point	0.043 (33)	-6.4 (193)	-4 (62)	-5.8 (17)	-6 (-118)	-6.5 (-123)	-6.7 (219)
NO_2	Regional	—	—	—	—	—	—	—
	Point	0.042 (-21)	-6.2 (244)	-3.1 (53)	-5.4 (-12)	-6 (-199)	-6.2 (-173)	-6.7 (290)
	Mobile	0.126 (-50)	-4.8 (-133)	-7.4 (-670)	-6.6 (-82)	-6.1 (-35)	-6.4 (-58)	-7.4 (-190)
	Area	0.163 (-26)	6.5 (-91)	14.3 (-2242)	15.7 (-145)	10.8 (-85)	12 (-95)	11.5 (-171)
	Total	0.012 (-25)	-2 (-494)	-2.4 (-207)	-2.1 (-55)	-2.2 (-38)	-2.3 (-64)	-2.8 (-412)

Supplemental Figures

Figure A3.1. Maps of baseline health rates used in the health impact functions.

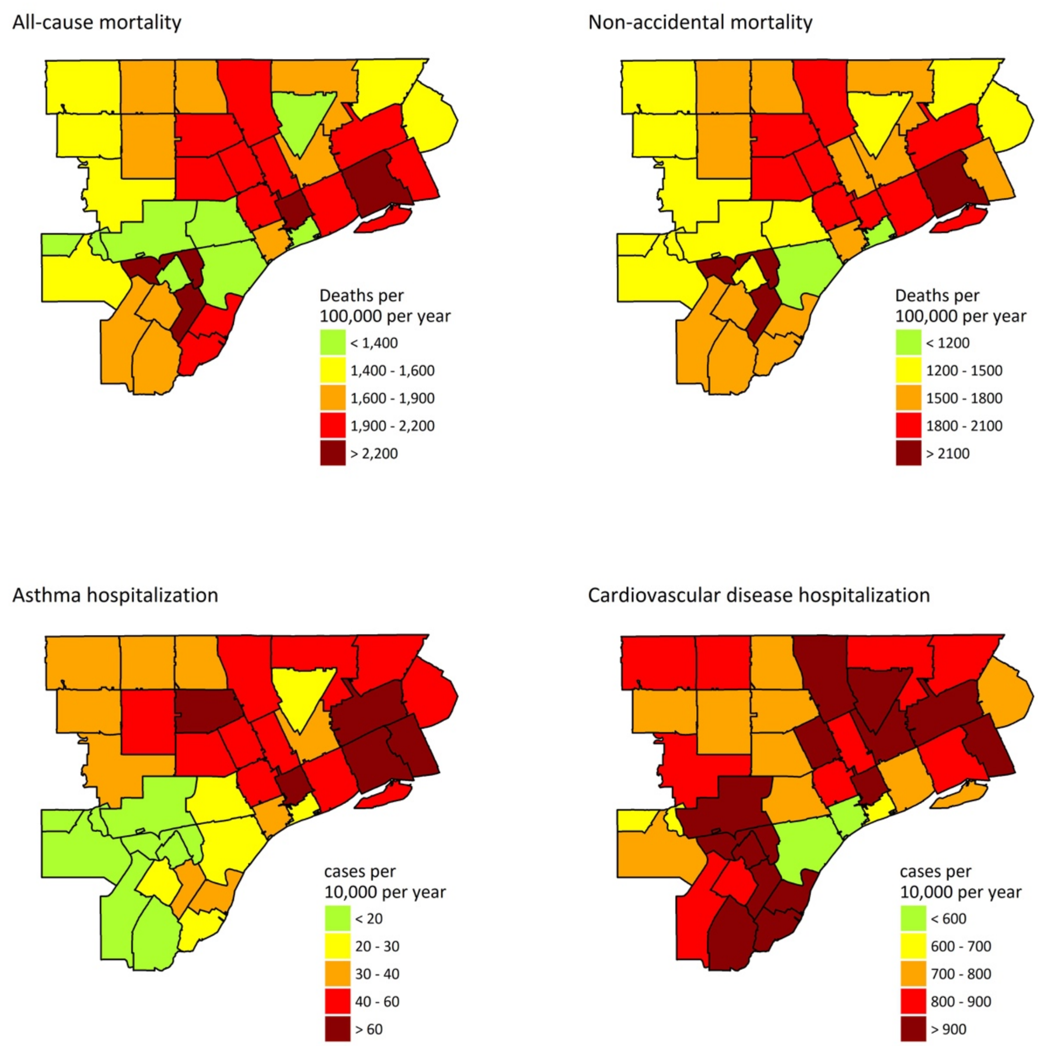


Figure A3.1 (continued). Maps of baseline health rates used in the health impact functions.

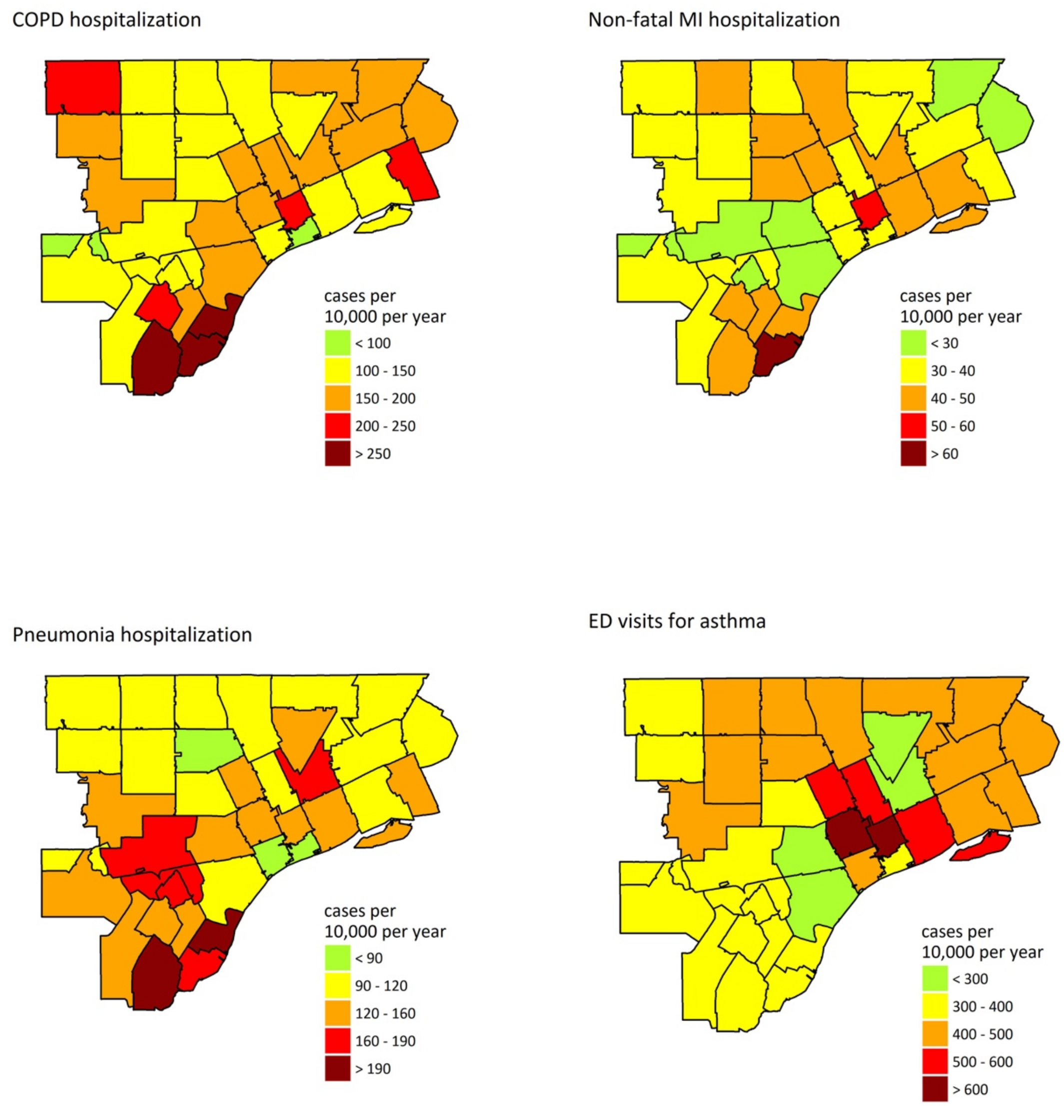


Figure A3.2. Maps of SES variables used to rank census blocks when calculating the concentration index.

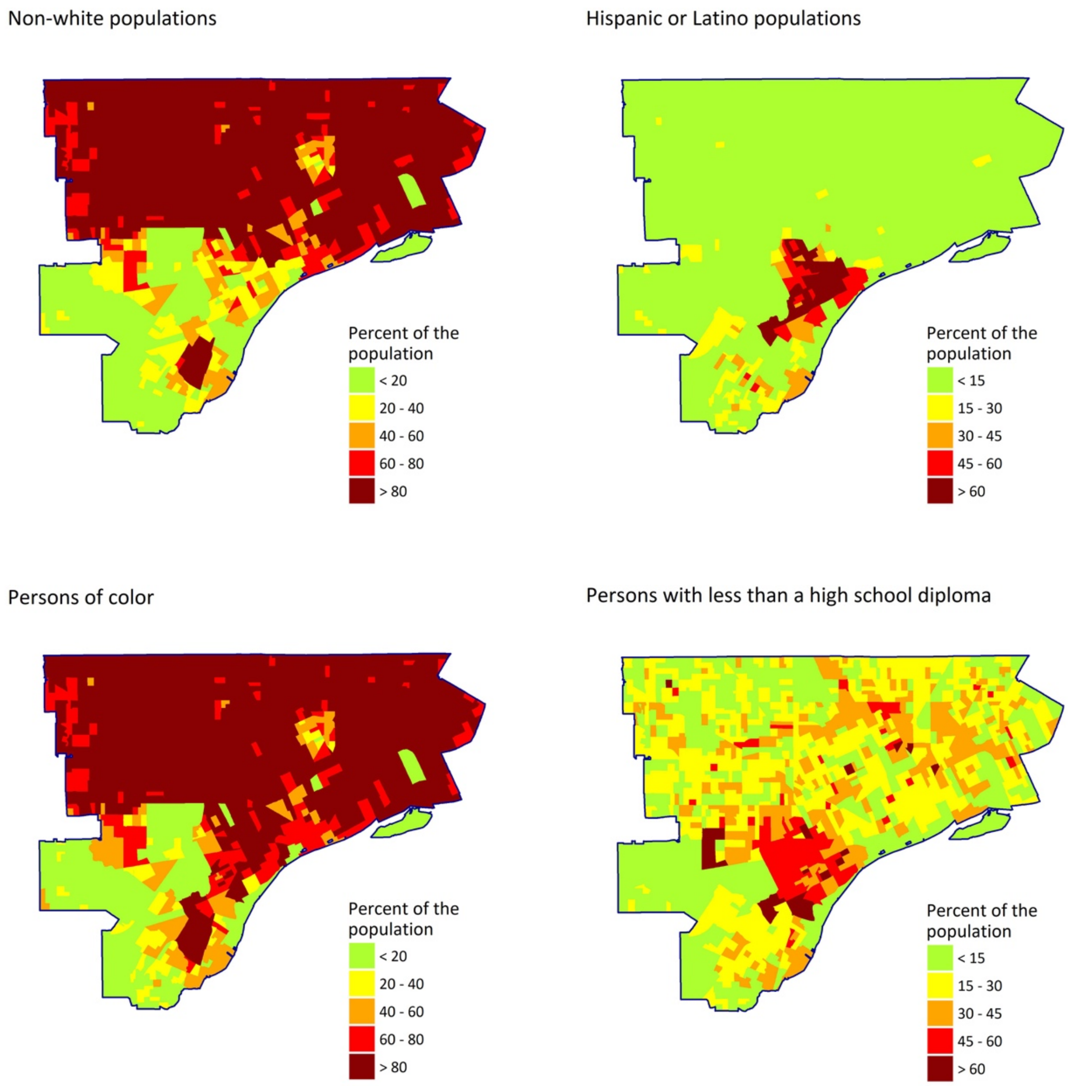


Figure A3.2 (continued). Maps of SES variables used to rank census blocks when calculating the concentration index.

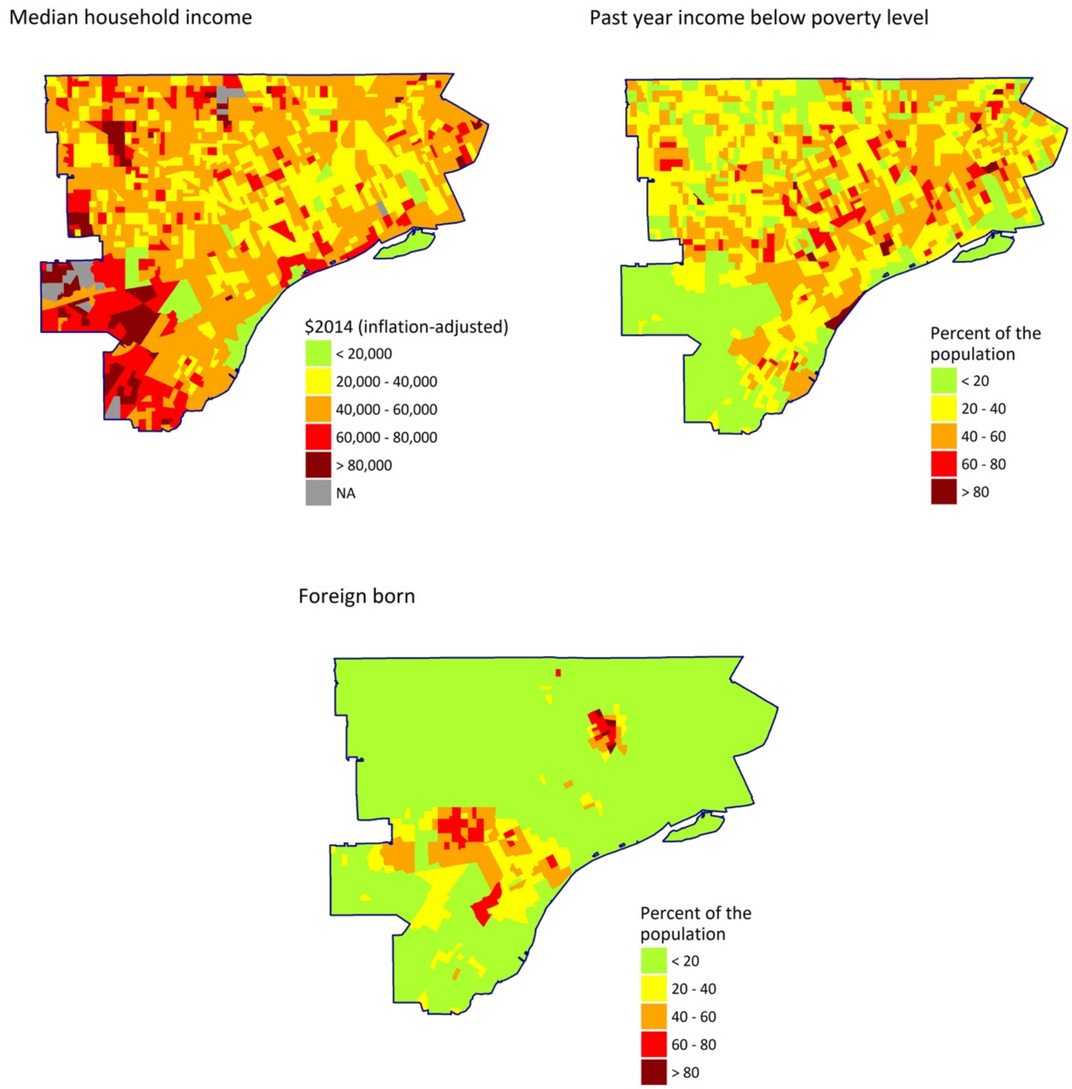


Figure A3.3. Comparison of the distributions of measured daily mean SO_2 concentrations at the Southwest High School monitor (2011-2015) and modeled FRESH-EST receptors within 150 m of the monitor. K-S tests for each receptor are all non-significant ($p > 0.05$)

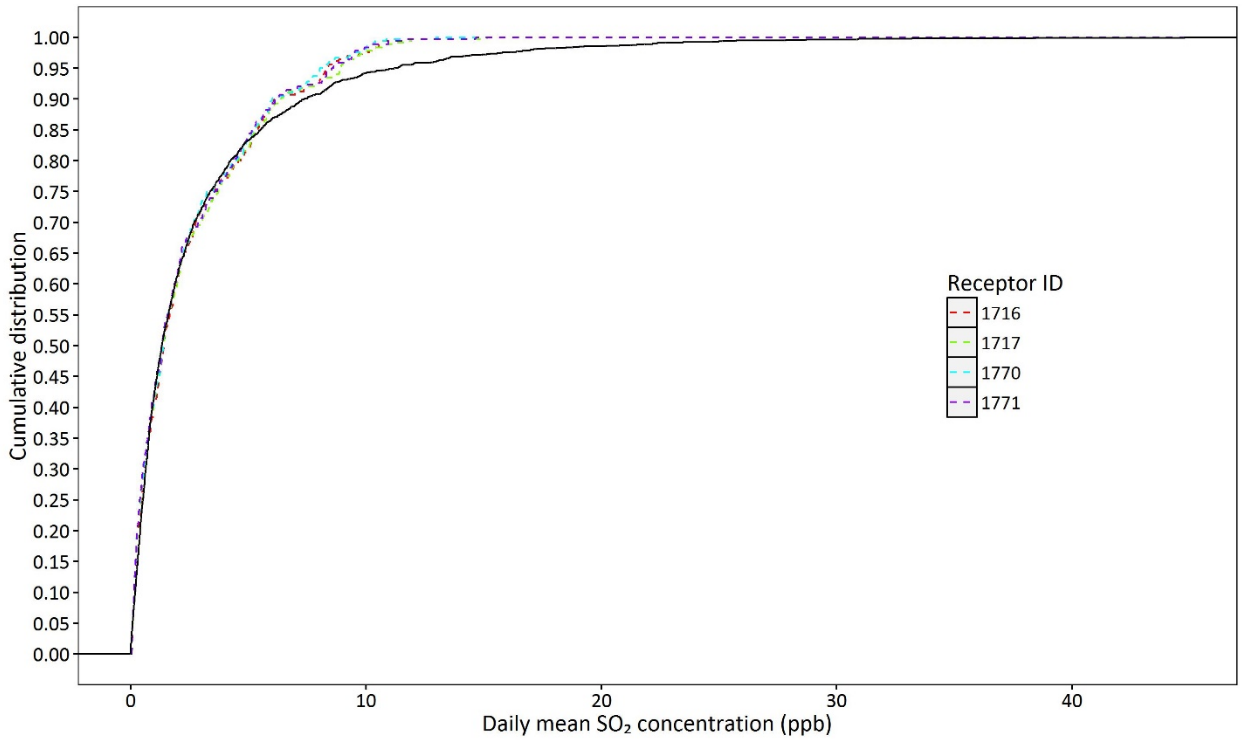


Figure A3.4. Daily concentrations of NO_2 (daily mean, ppb), O_3, (daily 8-hour max, ppb), and $PM_{2.5}$ (daily mean, μg/m^3) averaged across monitors in the Detroit, MI area.

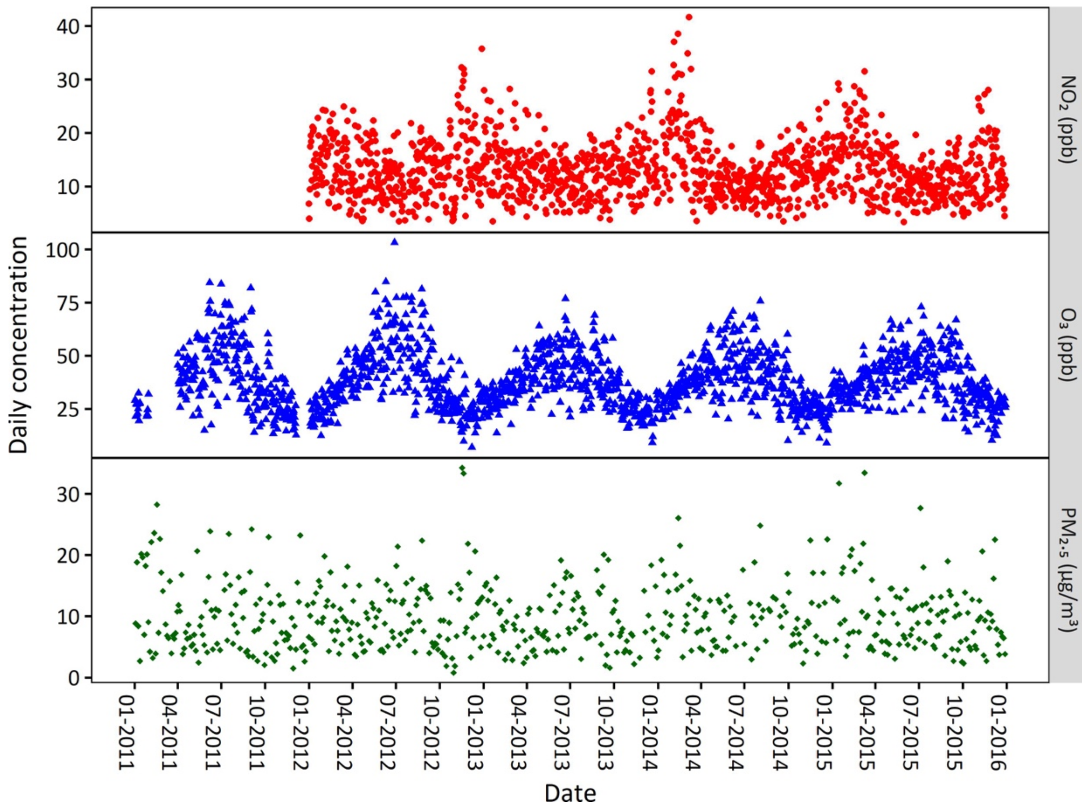


Figure A3.5. Annual diesel particulate matter (DPM) concentrations (A, µg/m^3) and excess cancer risk (B, excess cases per 10^6) due to DPM exposures measured at the census block level.

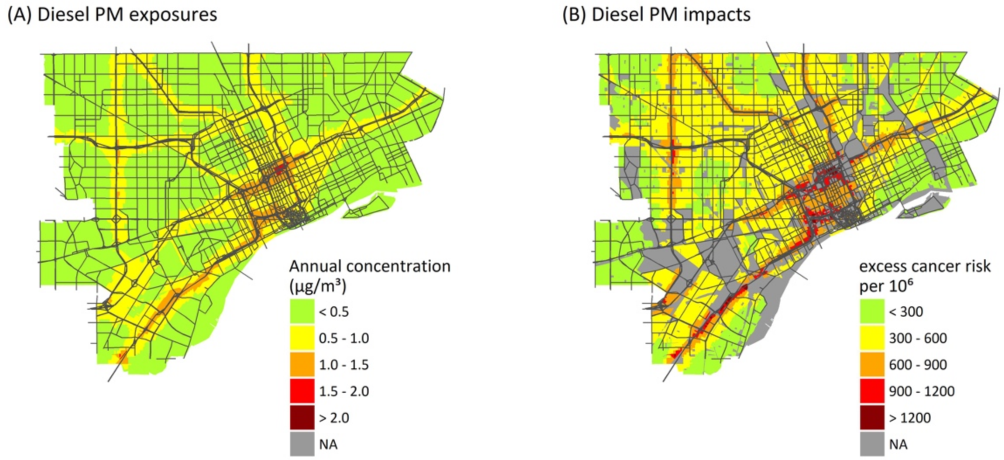


Figure A3.6. Maps showing the burden of disease (as DALYs per 10,000 per year) attributable to total exposures of (A) $PM_{2.5}$, (B) ozone, (C) SO_2, and (D) NO_2. The sub-region of the study area that is in non-attainment of the SO_2 National Ambient Air Quality Standard is shown (blue polygon).

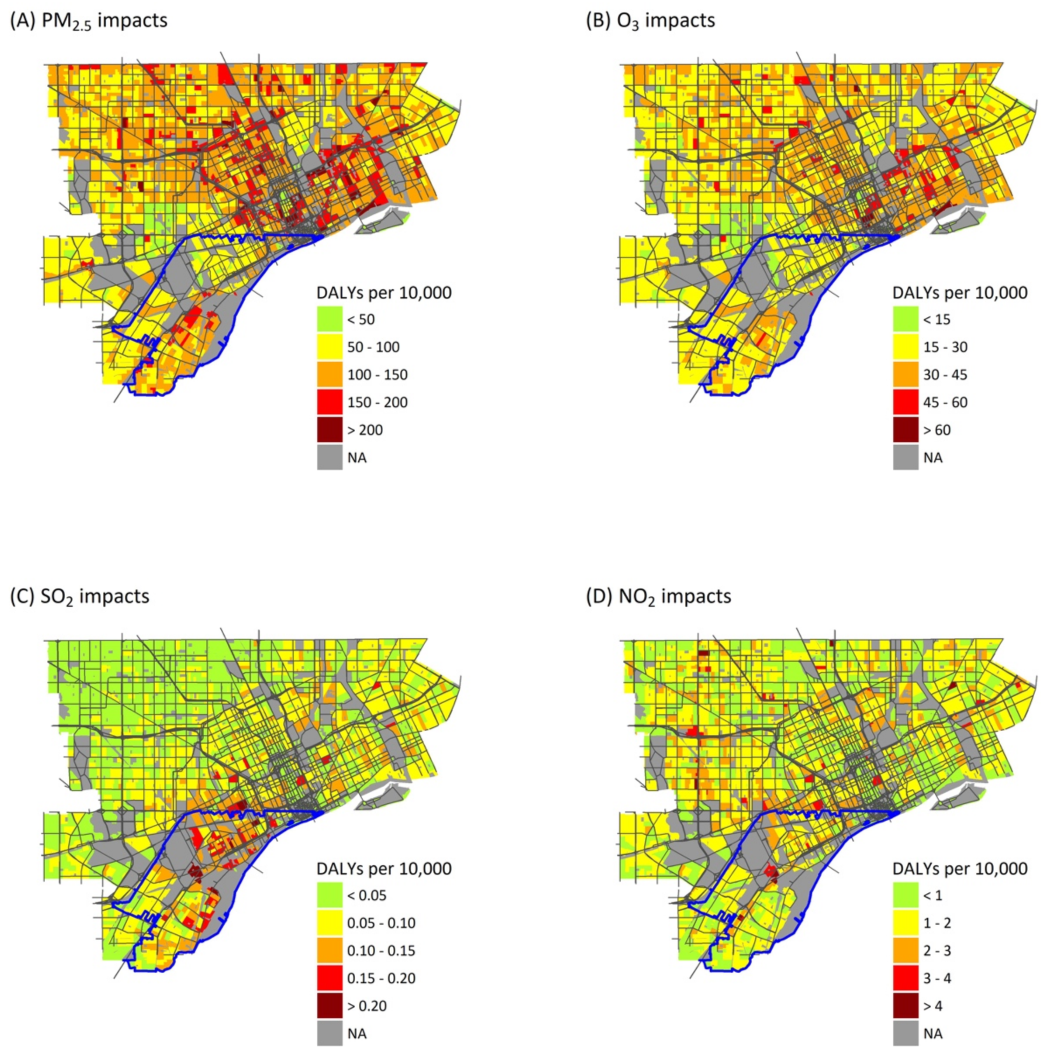
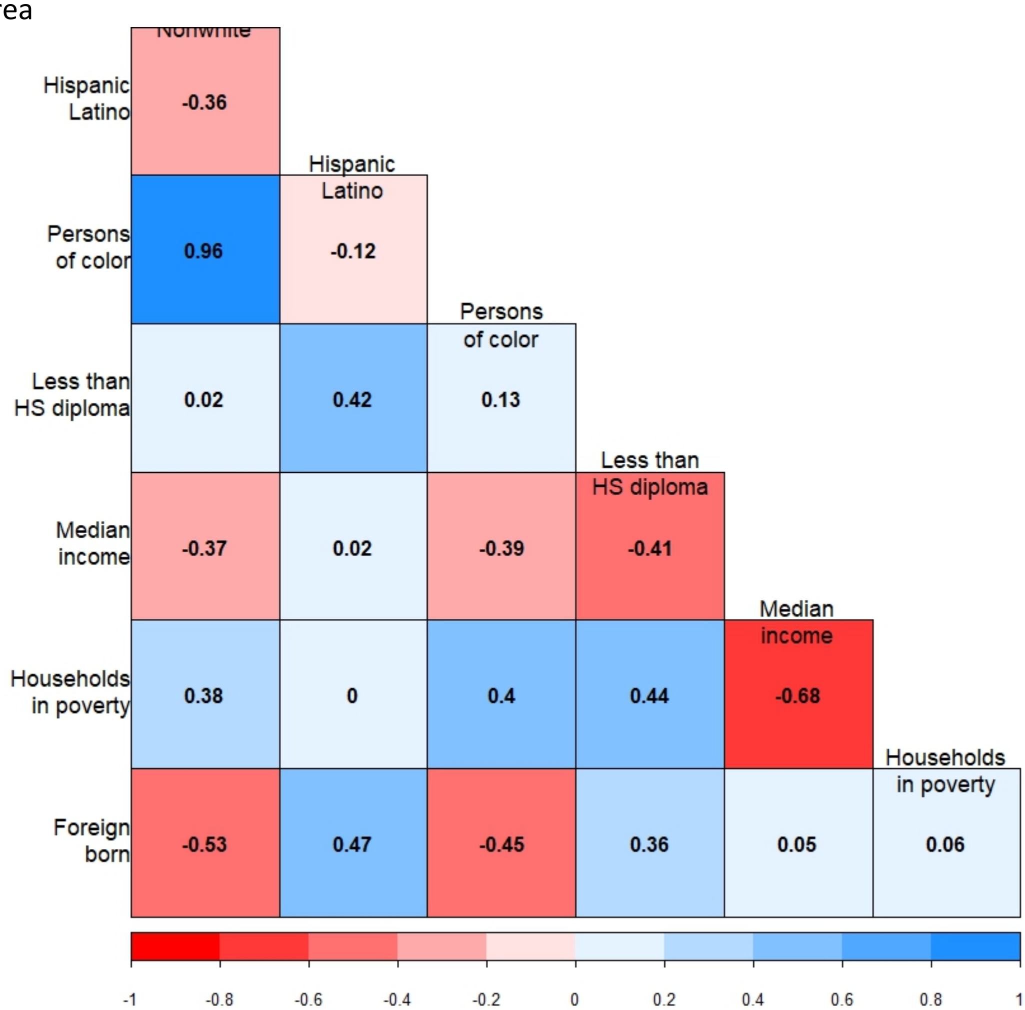


Figure A3.7. Correlations between block-level demographic and socioeconomic variables in the study area



Chapter 4

AIR POLLUTANT STRATEGIES TO REDUCE ADVERSE HEALTH IMPACTS AND HEALTH INEQUALITIES: A QUANTITATIVE ASSESSMENT FOR DETROIT, MICHIGAN

Abstract

The development of air quality management (AQM) strategies provides opportunities to improve public health and reduce health inequalities. This study evaluates health and inequality impacts of alternate SO_2 control strategies in a section of southeast Michigan (including Detroit), a designated non-attainment area. Control alternatives include uniform reductions across sources, ranking approaches based on total emissions and health impacts per ton of pollutant emitted, and optimizations that meet concentration and health goals. Each strategy is evaluated in terms of ambient concentrations, health impacts, and the inequality in health risks using dispersion modeling and quantitative health impact assessment (HIA). The health burden attributable to SO_2 emissions in the study area falls primarily among children and includes 70 hospitalizations and 6,000 asthma-related respiratory symptom-days annually, equivalent to 7 disability-adjusted life years (DALYs). The health burden disproportionately falls on Hispanic/Latino residents, residents with less than a high school diploma, and foreign-born residents. Control strategies that target smaller facilities near exposed populations provide the greatest benefit in terms of overall health burden reductions and the inequality of attributable health risk; conventional strategies that target the largest emissions sources can increase

inequality and provide only modest health benefits. The assessment is novel in using spatial analyses that account for urban scale gradients in exposure, demographics, vulnerability and population health. The analysis shows quantitative HIA methods can be used to develop AQM strategies that simultaneously meet environmental, public health, and environmental justice goals, advancing AQM beyond its current compliance-oriented focus.

Introduction

Background

Air quality management (AQM) is an iterative process that involves setting standards for air quality, designing and implementing control strategies to achieve these standards, and then assessing air quality status and progress towards these standards (NRC, 2004). In the USA, the operative standards used by states and the federal government are the National Ambient Air Quality Standards (NAAQS), which are intended to be protective of public health with an adequate margin of safety for sensitive subpopulations (NRC, 2004). Currently, AQM focuses on compliance with these standards. However, this may not provide the desired level of public health protection for several reasons. First, NAAQS compliance is based on concentrations measured at a limited number of fixed monitoring stations, which may not reflect the spatial variation in concentrations and the true exposure of the population (Levy and Hanna, 2011; Matte et al. 2013). Second, the NAAQS may fall short of protecting exposed and susceptible or vulnerable groups. Susceptibility refers to characteristics that may increase the adverse response to an exposure, e.g., underlying respiratory disease, and vulnerability refers to characteristics that reduce the ability to avoid or mitigate high exposures, e.g., low socioeconomic status (O'Neill et al. 2012, Sacks et al. 2011). Susceptibility and vulnerability can vary spatially, and subpopulations that have both high vulnerability and high exposure are more likely to experience adverse health impacts than the general population. Third, it is challenging or perhaps impossible to select a sufficiently protective regulatory standard when no effect threshold (i.e., a level below which health effects do not occur) has been identified. Ambient air quality standards are informed by integrated science assessments (previously called "criteria documents") and staff papers which summarize and synthesize the exposure, toxicological, and epidemiological literature, but ultimately, the designation of the standard is a policy decision made by the US EPA administrator (NRC, 2004). Additional concerns for AQM strategies based on NAAQS compliance include the single pollutant approach (i.e., the exclusion of cumulative impacts), delays in attaining compliance (in part due to the need for multiple years of monitoring data), and the technical, administrative, and legal steps involved in establishing and implementing policies to attain the NAAQS.

Health impact assessment (HIA) uses a comprehensive approach to evaluate health impacts that arise from programs, projects, or policies (Bhatia et al. 2014; Dannenberg, 2016). HIA is becoming an accepted approach for estimating the health impacts of air quality and the benefits of AQM options, and many HIA tools have been developed to facilitate HIA analyses (Anenberg et al. 2015). HIAs for AQM can incorporate information from air quality models, ambient air monitoring, population demographics, environmental epidemiology, and other sources. In a "full" HIA which is intended to inform a policy decision and includes screening and scoping of alternatives, assessment of impacts, development of recommendations, reporting, and evaluation (NRC 2004), quantitative assessments of morbidity and mortality attributable to pollutant exposures would be complemented by qualitative analyses evaluate the benefits and adverse impacts that are not included in the quantitative assessment. In this application, we focus on the more narrow quantitative assessment of impacts attributable to air pollutant exposures, following the approach used by US EPA in their Regulatory Impact Analyses (e.g., US EPA 2010a). Quantitative HIAs have been used to examine potential impacts from power plants and other source types at regional and national levels (e.g., Buonocore et al. 2014; Fann et al. 2009). Impacts of specific pollution sources at local or urban levels can be examined given appropriate input data, e.g., baseline health outcome incidence rates and exposure estimates (Hubbell et al. 2009).

Inequality metrics quantify the distribution of health impacts or benefits across space (e.g., census blocks) or groups (e.g., minority populations). These metrics can indicate how an AQM option affects the outcome distribution (Maguire and Sheriff, 2011), key information for environmental justice analyses that evaluate whether certain groups experience disproportionate adverse effects from environmental hazards (Brulle and Pellow, 2006). Preferred indicators or metrics for environmental justice analyses have been identified (Levy et al. 2006). For example, the Atkinson Index (AI), originally developed as an income inequality parameter, evaluates inequality across individuals or units (e.g., census blocks). It includes a subjective “inequality aversion” parameter, which accounts for societal attitudes towards inequality, and it can be decomposed to examine differences between groups, e.g., race and ethnicity groups (Levy et al. 2006). Larger AI values indicate greater inequality in the distribution of risk. Another inequality metric, the concentration index (CI), examines the distribution of health burdens across population subgroups ranked by social status (O'Donnell et al. 2008). The CI plots the cumulative distribution of health risks against the cumulative ranking of census blocks ordered by the selected demographic or SES variable, and is calculated as the area under the 1:1 line minus the area under the concentration curve. Negative CI values indicate that less socially advantaged groups carry disproportionately heavier health burdens. This metric has been used to evaluate a variety of environmental hazards, e.g., $PM_{2.5}$, ozone, traffic density, and proximity to toxic release sites (Cushing et al. 2015; Sadd et al. 2011; Su et al. 2012, 2009). Despite their usefulness in quantifying environmental inequalities, inequality metrics are not routinely used in regulatory or other analyses (Harper et al. 2013).

Determining whether an AQM strategy will attain ambient standards, minimize health impacts and reduce inequalities requires combining health impact metrics with inequality metrics and possibly other information. For example, a study examining power plant emissions in the U.S. found that controlling sources with the largest health impacts per unit emissions conferred the greatest health benefits and inequality reductions (Levy et al. 2007). A study investigating controls for $PM_{2.5}$ and ozone precursors in Detroit, MI showed that a multipollutant approach achieved better health and inequality benefits compared to single pollutant strategies (Fann et al. 2011; Wesson et al. 2010). These examples combined quantitative health impacts and inequality metrics either using large study areas with coarsely-resolved exposure and health data (Levy et al. 2007) or pollutants with low spatial variability, e.g., ozone and $PM_{2.5}$ (Fann et al. 2011; Wesson et al. 2010). AQM strategies evaluating health impacts and inequalities have not been applied to pollutants that have significant spatial-variability at the intra-urban scale, despite their considerable promise to benefit populations and their relevance to many environmental justice applications.

Objectives

This study investigates emission control strategies aimed at reducing the burden of disease and health burden inequalities. Alternative strategies are formulated and evaluated in terms of ambient concentrations, total health benefits, and the distribution of health impacts across an urban population. The analysis quantifies the potential trade-offs between emission reductions, health impacts, and inequality, and demonstrates how health burden and inequality metrics might be used at an urban scale and in a regulatory context.

Methods

HIA methods are used to estimate the burden of disease attributable to SO_2 exposures in southeast Michigan. Two sets of emission control strategies are considered. The first reduces current (ongoing) emissions at major sources in the area, and thus represents actual or typical exposure to SO_2 in the study area. The second examines alternatives to a proposed state implementation plan (SIP) that follows EPA guidance, which starts with the maximum allowable emissions based on existing and revised permits (US EPA, 2005); this analysis highlights issues related to using the maximum allowable emissions in SIP development. The study area includes the portion of Wayne County designated as non-attainment for the 2010 SO_2 ambient air quality standard (MDEQ, 2016) and is extended to also include Detroit and several adjacent cities (Figure 4.1) which were shown in a previous analysis to have substantial health burdens due to point source emissions of SO_2 (Chapter 3). The control strategy options, evaluative metrics, and study area are described below. Additional information regarding the HIA methods and data sources is provided in Appendix A3.

SO_2 emissions inventory and estimates of population exposures

SO_2 emission estimates are derived from 2010 to 2014 stack-level data retrieved from the Michigan Air Emissions Reporting System (MDEQ, 2001). For major sources in the region (i.e., sources emitting more than 100 tons of SO_2 per year), emissions are modeled at the stack level; for other sources, facility-level emissions are used. Eight major SO_2 sources, each emitting more than 100 tons per year, fall within the SO_2 non-attainment area (Figure 4.1): three coal-powered electrical generating facilities (DTE Trenton Channel, DTE River Rouge, Dearborn Industrial Generation); two large steel facilities (US Steel at Zug Island and Ecorse, Severstal/AK Steel); two lime and coke facilities (EES Coke, Carmeuse Lime); and an oil refinery (Marathon). None of these facilities uses add-on control technologies for SO_2 (MDEQ, 2016). The analysis also includes 126 other point source facilities in the area, including the DTE Monroe power plant. This facility, located approximately 60 km south of Detroit, is the state's largest coal-fired power plant (3,300 MW) and recently installed scrubbers to significantly reduce SO_2 emissions. These nine sources account for 92% of SO_2 point source emissions in southeast Michigan. Because reported emissions fluctuate annually, emissions are averaged for the 2010 to 2014 period. In cases, only the more recent data were used to account for known changes over time. These represent current or "base case" emissions.

Population-level exposures are estimated using the Framework for Rapid Emissions Scenario and Health impact Estimation (FRESH-EST), a software package that allows rapid assessment of exposures and health impacts due to point source emissions for a given areal unit, e.g., census blocks (Milando et al. 2016). Briefly, ambient SO_2 concentrations attributable to point source emissions are estimated at a set of discrete locations ("receptors") using a source-receptor or "transfer coefficient" matrix developed using the AERMOD dispersion model (Cimorelli et al. 2005), local meteorology, and an adaptive receptor grid (200 m spacing near major sources, and 1 km spacing elsewhere). FRESH-EST interpolates from the receptor grid to a 25 m raster using inverse-distance weighting, and uses the average of raster cells overlapping census block polygons to estimate exposure concentrations. FRESH-EST includes an optimization module to minimize point source emissions to attain specified receptor concentrations or maximize health benefits, subject to other constraints.

Census blocks are used as the spatial unit of analysis, balancing the need for accurate exposure assessment with the available population and baseline health data (Batterman et al. 2014). Time-activity patterns that account for working and living in areas with different pollutant levels are not considered. Although this may lead to exposure measurement errors and possible biases in health impact estimates, the epidemiological studies underlying the concentration-response coefficients mostly rely on area monitors and residence locations to assign exposures.

SO_2 emissions control alternatives

Strategies to reduce emissions of SO_2

Baseline emissions from point sources are used to represent "current" exposures and health impacts attributable to these sources under current operating conditions; this is the base case strategy designated "S0". Five types of strategies are considered (Table 4.1). Each is evaluated at six levels that represent 15, 30, 45, 60, 75, and 90% reductions in aggregate SO_2 emissions from baseline levels. Individual major sources are allowed to reduce emissions by up to 90%, the maximum control attainable with add-on technologies, e.g., flue gas desulfurization (Srivastava and Jozewicz, 2001). We focus on reducing emissions at the eight major sources located within the non-attainment area.

The simplest approaches apply uniform reductions across all sources (strategy S1) or controls at the largest facilities first (S2) to meet reduction goals. The "health impact ranking" strategy (S3) ranks sources by the health impacts per ton of SO_2 emitted, and imposes reductions on the highest ranked sources first until the emissions target is met (Levy et al. 2007). Strategies S4 and S5 minimize receptor concentrations and maximize health benefits (i.e., minimizing disability-adjusted life years; DALYs), respectively, using the FRESH-EST optimization module with constraints that limit emissions at each source (allowing between 10 and 100% of baseline emissions) and that attain the emissions target (summed across major sources). For all of these strategies, emissions at DTE Monroe and the 125 minor facilities remain at baseline.

SIP base case, control strategy, and optimized alternatives

The SIP strategy proposed by Michigan Department of Environmental Quality (MDEQ) started with the maximum allowable SO_2 emissions and considered SO_2 monitoring data, dispersion modeling, and Reasonably Achievable Control Technology (RACT) analyses (MDEQ, 2016). It identified five culpable sources after conducting a hotspot analysis (DTE River Rouge, DTE Trenton Channel, US Steel, EES Coke, Carmeuse Lime), and called for emissions reductions at the DTE plants and US Steel, the shutdown of specific boilers at the DTE plants, and the construction of a taller stack at Carmeuse Lime; no changes are required at EES Coke (MDEQ, 2016). In the "SIP maximum allowable case" (strategy S6), we use the existing maximum allowable emissions at major sources (MDEQ, 2016, pp. 15–16) and current emissions at other sources (as described in Section 2.1). The "SIP control strategy" (S7) implements the MDEQ SIP strategy (MDEQ, 2016) with other emissions unchanged from S6.

Two additional alternatives that attain the overall SO_2 reduction specified in the SIP (26,418 tons per year) are evaluated. Strategy S8 minimizes the maximum receptor concentration, and strategy S9 maximizes health benefit. Both allow emissions reductions at only the five culpable sources identified by MDEQ; stack heights are unchanged. For strategies S7-S9, the SIP maximum allowable case (S6) serves as the comparison (i.e., base case) strategy.

Health impact assessment

Outcomes associated with SO_2 exposure include hospitalizations for respiratory diseases, asthma-related emergency department visits, and asthma symptom-days among children.

FRESH-EST uses health impact functions to estimate the numbers of these outcomes attributable to SO_2 exposures, similar to those in other HIA tools (US EPA, 2015). Only health outcomes for which a causal relationship with SO_2 exposure has been established are considered, as determined by US EPA (US EPA, 2008, 2016a), which may under-predict the true health burden. The analysis assumes a no-threshold concentrations-response (CR) relationship between SO_2 exposures and health effects, consistent with US EPA conclusions regarding the lack of evidence of a population-level exposure threshold (US EPA, 2016a, 2008). Health impacts are calculated using 24-hr average SO_2 concentrations, which is consistent with the epidemiological studies from which CR coefficients are drawn. Uncertainty in the health impact estimates, represented as a 95% confidence interval, is estimated using the uncertainty around the CR coefficient, which has been shown to account for substantial portion of the total uncertainty in quantitative health impact estimates (Chart-asa and Gibson, 2015).

Evaluative metrics

Control strategies are evaluated using concentrations, health impact, and inequality metrics. For the concentration metric, the analysis uses the fourth highest 1-hour daily maximum SO_2 concentration at non-fenceline receptors. This is similar but not identical to the form of the SO_2 NAAQS definition, which uses the 3-year average of the annual fourth highest 1-hour daily maximum concentrations (US EPA, 2010b). We use concentrations for a single year because the reduced form model employed by the FRESH-EST tool uses meteorology for a single year (2012). Health impacts are reported as the number of attributable cases and DALYs, which aggregate the health outcomes into a single summary metric based on time lost to poor health

(Murray, 1994). DALYs provide a measure of the total health burden, including hospitalizations and asthma exacerbations in older adults and children, respectively, by more heavily weighting more severe but less frequent outcomes, e.g., hospitalizations, than more frequent but less severe outcomes, e.g., days with asthma symptoms. Disability weights and durations for DALYs are drawn from existing studies (CDC, 2012; de Hollander et al. 1999; Murray, 1994; Ostro, 1987). Attributable cases are monetized using values (in 2010$ adjusted to a 2020 income level) reported by the US EPA in the most recent Regulatory Impact Assessment for fine particulate matter (US EPA, 2012).

Inequality of the health burden is examined using the AI and the CI. For the AI, the inequality parameter is set to 0.75 following prior AQM work (Fann et al. 2011). For the CI, the required spatially-resolved demographic and SES data to rank the vulnerability of census blocks uses seven (block group level) variables from the 2014 5-year American Community Survey (Figure A3.2): percentage of the population that is non-white, Hispanic or Latino, persons of color, foreign born, or with less than a high school diploma; median household income (inflation-adjusted 2014 dollars); and percentage of households with past year income below the poverty level (US Census Bureau, 2014).

The inequality of the health burden is based on the risk of SO_2-attributable DALYs. The use of attributable (rather than total) DALYs helps assess whether the SO_2 reduction strategies result in “fair treatment” of all population subgroups, i.e., that each subgroup receives a benefit as a result of AQM actions (US EPA, 2016b). The mean estimate of DALYs generated by the health impact functions is used to assess health impact and inequality metrics.

Description of the study area and population

The study area includes a large section of Wayne County, Michigan, including the designated SO_2 non-attainment area (MDEQ, 2016) (Figure 4.1). A total of 1,140,000 people lives in the study area (US Census Bureau, 2014). Air pollution has been and remains an important environmental health concern for southeast Michigan residents. Due to its industrial legacy, the study area contains many large sources that are primarily responsible for population exposures to SO_2. Residents in the study area are likely vulnerable or susceptible to these SO_2 exposures. The study area has higher proportions of residents that identify as persons of color (68%) and residents living below the poverty line (31%) compared to the state of Michigan as a whole (23.9 and 23.7%, respectively) (US Census Bureau, 2014) Health disparities between the study area and the state as a whole are significant, particularly for diseases associated with air pollution, e.g., the annual rate of asthma hospitalizations in the study area (37.9 per 10,000) is more than twice the state average (14.8 per 10,000) (MDHHS, 2015).

Results

Exposures and burden of disease

SO_2 exposures across the study area vary considerably. Figure 4.2A maps annual average concentrations for the base case (S0). Levels are highest in southwest Detroit (near the center of the study area) where several major sources are clustered. The 4th highest 1-hour daily maximum concentration occurs in this area, but areas to the north also experience high concentrations (Figure 4.2B). (The 4th highest 1-hour daily max concentrations shown are not necessarily contemporaneous.) Table 4.2 summarizes the distribution of hourly SO_2 concentrations at receptors, daily mean SO_2 concentrations at the census block level, and daily 1-hour maximum SO_2 concentrations at Southwest High School (SWHS). Comparisons of predicted and observed daily mean SO_2 concentrations at the SWHS monitor, which recorded the highest SO_2 levels in the area, showed no significant differences (K-S test, $p > 0.05$, Figure A4.1), suggesting that point source emissions account for SO_2 concentrations in the area and that the dispersion model replicates the observed distribution.

The burden of disease from SO_2 falls mostly among children. For the base case, health impacts among residents in the study area include 7 hospitalizations for asthma, 95 ED visits for asthma, and over 6000 days with asthma-related respiratory symptoms (i.e., exacerbations; Table 4.3). This is equivalent to $2.7 million in monetized impacts each year, most (>90%) of which is from asthma-related respiratory symptom-days. Asthma exacerbations increase 4-fold using a Detroit-specific CR coefficient (Batterman et al. manuscript in preparation), reflecting the potentially higher vulnerability of Detroit children to SO_2 exposures. These estimates only reflect health impacts from SO_2 exposures and do not include health impacts that would result from the formation of secondary aerosols (e.g., $PM_{2.5}$) from SO_2, which may be substantially exceed the impacts from SO_2 alone (US EPA, 2010a).

Health impacts by sources

Table 4.4 lists SO_2 emissions, attributable health impacts as DALYs per year, and annual health impacts per 100 tons of SO_2 emitted by the major sources, information which guides the emissions and health-oriented ranking strategies (S2 and S3). (For comparison, the table includes DTE Monroe, which was excluded from the control strategies as its location is outside the non-attainment area.) The 125 minor sources emit 8% of the SO_2 in the inventory and cause 11% of the health burden. Importantly, rankings of major sources by emissions, DALYs and health impacts differ, e.g., the highest ranked source for total emissions (excluding DTE Monroe) is DTE Trenton Channel; the top source for DALYs is US Steel, and the top source for DALYs per 100 tons SO_2 is Carmeuse Lime. Although SO_2 emissions from Carmeuse Lime, Detroit Industrial Generation and Severstal/AK Steel are relatively small (< 800 tons per year each), their proximity to residential neighborhoods and low stack heights increase SO_2 exposure per ton of emissions, thus increasing the burden attributable to these facilities.

Comparison of SO_2 control strategies

Fourth highest 1-hour daily maximum SO_2 concentration

The "peak" (4^{th} highest 1-hour daily maximum) SO_2 concentrations for six control strategies are shown in Table 4.5. For the base case (0% reduction), the peak (79.5 ppb) exceeds the NAAQS concentration (75 ppb). At each SO_2 reduction target, the "largest emissions first" (S2) approach gives the highest peak concentration; the "receptor-concentration optimization (S4) gives the lowest. With full (90%) reductions, the peak concentration falls to 56.2 ppb. Despite the high level of SO_2 emission reductions, peak concentrations do not drop further because emissions from excluded facilities (DTE Monroe and the minor facilities), which emit nearly 60% of the total SO_2 emissions in the area combined, are unchanged from baseline.

Total attributable health burden

Trade-offs between health improvements (DALYs per year) and inequality (AI) are depicted in Figure 4.3 for each control strategy type. (Comparable figures showing the tradeoffs between health impacts and the CI are provided in Appendix A4.) The health burden decreases from 7.0 DALYs per year for the base case to 2.6 DALYs per year for 90% emission reductions (Table 4.6). The health burden falls less than 90% since emissions at DTE Monroe and the minor point sources do not change. While any emission reduction lowers the health burden, some strategies are more effective. The uniform reductions strategy (S1) provides nearly linear improvements, as expected. For low to moderate emissions reductions (15 – 45%), reducing emissions at sources with the highest impacts per ton of emissions (S3) yields greater health benefits than the uniform percentage (S1) and the minimal concentration (S4) strategies. Although advantages diminish beyond 60% reductions, strategy S3 still outperforms S1 and S2 due to its emphasis on reducing emissions at sources near large populations, i.e., sources with the highest health impact per unit emissions (Table 4.4). The concentration optimization strategy (S4) outperforms the uniform reductions approach for smaller reduction targets (15-45%), but benefits diminish at higher reduction goals. Results for health ranking (S3) and health optimization (S5) strategies are nearly identical for 30, 45, and 60% reduction goals, and the simpler health-based ranking approach (S3) achieves near-optimal results.

Inequality of health impacts

Both inequality metrics suggest there is an unfair distribution in SO_2-related health impacts in the study area (AI for the base case = 0.136). The CI indicates that the SO_2-related health burden tends to disproportionately affect areas with high proportions of residents who are Hispanic or Latino, have less than a high school diploma, or are foreign-born (Table 4.6; Figure A3.2). In the study area, these variables are moderately correlated (Pearson R: 0.35 – 0.47), and census blocks with the highest proportions of Hispanic or Latino residents coincide with the highest SO_2 exposures (southwest Detroit, Figure 4.2A, Figure A3.2).

All of the strategies with one exception reduce the inequality of adverse health impact risks associated with SO_2 (Figure 4.3, Table 4.6). While the largest-emissions first approach (S2) reduces the total health burden (as DALYs), this strategy increases inequality, a result of this strategy increasing the relative importance of SO_2 "hotspots" produced by smaller facilities. The lowest inequality occurs for the health impact optimization (S5) with a 75% reduction in total emissions (AI = 0.116, DALYs per year = 2.58). Increasing removals to 90% slightly lowers impacts (DALYs per year = 2.57) though inequality slightly increases (AI = 0.117) since reductions at all sources tends to increase inequality (as discussed above). Possibly the most striking result in Figure 4.3, however, is the very large improvement in inequality and DALYs yielded by a very modest (15%) reduction of SO_2 emissions with the health impact optimization (S5) strategy due to the high benefits per ton removed for the targeted sources (Table 4.4); this strategy reduces emissions by 90% at AK Steel, Marathon, Dearborn Industrial Generation, Carmeuse Lime, and US Steel, and by 60% at EES Coke, while emissions at DTE Trenton Channel and DTE River Rouge are unchanged.

The distribution of benefits from SO_2 reductions across social groups is strategy-dependent. The largest changes in the CI at intermediate SO_2 reduction targets occur for the largest-health-impacts-first (S3) and the health optimization (S5) strategies. These strategies are shown to benefit Hispanic/Latino, low educational attainment, and foreign-born populations; this is important because these groups bear heavier burdens in the base case (Table 4.6). The "percentage of the population of persons of color" variable does not indicate a disproportionately high health burden from SO_2 because a majority of individuals (68%) in the study area identify as non-Hispanic Black or Hispanic/Latino (US Census Bureau, 2015); aggregating these groups using a single variable ignores important demographic patterns within the study area.

SIP versus optimized strategies

Since maximum allowable emissions were approximately twice that of the actual emissions, the SIP maximum allowable case (S6), SIP (S7), and optimized (S8 and S9) strategies gave considerably higher concentrations and exposures (Table 4.7) than those using actual emissions (Tables 4.2 and 4.5). The peak concentration (111 ppb for strategy S7) differs from the SIP (74 ppb; (MDEQ, 2016, p. 34) due to differences in receptor grids, years modeled, and the treatment of background. (A more detailed "hotspot" analysis, as performed by MDEQ, would be needed to ensure the alternative strategies achieve the NAAQS and comply with US EPA criteria.) Like strategies based on actual emissions, reducing the maximum allowable emissions yields health benefits, and all strategies based on maximum allowable emissions reduced inequalities (Figure 4.4). The SIP control (S7) and the concentration optimization (S8) strategies performed similarly; the health optimization alternative (S9) outperformed both of these strategies with respect to exposures, health benefits and inequality. Note that strategies S7, S8 and S9 reduced emissions by the same amount (26,418 tons per year). Based on the CI, the health-based approach is particularly beneficial for disproportionately impacted populations, e.g., areas with high proportions of Hispanic or Latino residents (Table 4.8).

Discussion

Health-based AQM strategies can yield large decreases in health burdens and the inequality of health risks, performing better than current strategies that prioritize compliance with the NAAQS. In Detroit, reducing emissions at sources with the largest health impacts (S3, S5) achieved the greatest benefits in attributable health burden and inequality. These sources tend to be smaller and closer to densely populated areas. In contrast, strategies focusing on the largest sources (S2) only modestly reduced health burdens and increased inequality. These sources mostly have tall stacks, are far from populated areas, and their resulting concentrations tend to be low and well dispersed. While emission reductions at these large sources lessen the health burden across broad areas, it increases the relative importance of smaller sources, thus increasing inequality. The inefficiency of the largest-emissions-first strategy in terms of health benefits and its tendency to increase inequality is an important result that has not been emphasized elsewhere, in part because earlier studies primarily focused on total health risks rather than pollutant-attributable risks (Levy et al. 2007).

The trade-offs between emissions reduction, health burden and inequality demonstrated for the study area are scenario- and site-specific. Still, our findings appear broadly applicable. For example, a national assessment of power plants showed that reducing emissions at sources with the highest health impacts per ton of pollutant emitted maximizes improvements in health and inequality (Levy et al. 2007). Trends similar to those determined for Detroit are expected in other urban areas that have industry and residential areas interspersed.

Benefits of using quantitative HIA analyses in the air quality management process

The development of a control strategy represents a prime opportunity for reducing health burdens and disparities, which is not taken advantage of in the current compliance-oriented approach. For example, the Detroit SO_2 SIP submission specifies emissions reductions at three facilities and stack height increases at another (MDEQ, 2016), an approach derived following US EPA guidelines, negotiations with affected facilities, and RACT analyses. Unfortunately, this plan targets sources that have relatively low health impacts per ton of SO_2 emitted (Table 4.4), and it will not alleviate disparities associated with SO_2 exposures. This is supported by the "actual emissions" strategies (S1-S5), which better reflect current exposures than the SIP maximum allowable case (S6). While results in Figures 4.3 and 4.4 are not directly comparable (Figure 4.3 is based on health impact estimates using average or "actual" emissions and Figure 4.4 is based on health impact estimates using maximum allowable emissions; the relationship between “actual” and maximum allowable emissions is not consistent across sources), they each show that health-based strategies can yield bigger improvements in public health and health inequalities.

The use of the maximum allowable emissions is currently required for air quality modeling demonstrations of NAAQS attainment (US EPA, 2005). For the nine major SO_2 sources in Detroit, these maxima exceeded actual emissions by 1.6 to 4.0 times, depending on the source. In consequence, the use of maximum emissions greatly over-estimates health burdens and might not target the sources that actually cause the highest concentration, health or inequality impacts. The short-term (1-hr) NAAQS must be attained under all circumstance, so this rule is justifiable; however, a second analysis using actual emissions would improve the realism of exposure and health analyses and potentially result in healthier and fairer outcomes. Alternatively, the difference between actual and maximum allowable emissions could be reduced, perhaps to no more than a factor of 1.5, and then a single analysis could simultaneously demonstrate that a proposed SIP strategy attains the NAAQS, maximizes health benefits, and minimizes inequality.

Multipollutant AQM approaches also can increase both health and inequality benefits. An integrated and least-cost approach for $PM_{2.5}$ and ozone in Detroit using “population-oriented reductions” was predicted to attain standards, lower total health impacts and reduce inequality compared to strategies that addressed pollutants separately (Fann et al. 2011; Wesson et al.

2010). While we focused on a single pollutant, analyses of other pollutants could inform the evaluation and development of control alternatives.

Evolving towards more comprehensive and equitable air quality management

Reorienting AQM from standards compliance to consideration of site-specific health and inequality concerns is, in part, motivated by environmental justice and cumulative impact concerns. U.S. EPA is becoming increasingly concerned with the “fair treatment” of all social groups when implementing environmental policies, and this extends to the distribution of health benefits as a result of policy actions (US EPA, 2016b). The agency has expressed a preference for quantitative EJ analyses that complement other analyses in the rule making process (US EPA, 2016c). Several state and local regulators are also formalizing EJ activities, including permitting, compliance, enforcement, and monitoring (MPCA, 2015). These goals can be supported using the CI and other metrics. Our use of the SO_2-attributable burden in inequality assessments helps identify whether the benefits of emission control strategies are fairly distributed, and it highlight how some population groups (Hispanic and Latino populations) received fewer benefits under some of the strategies. Potentially, HIA tools and inequality metrics can show the rate of progress towards eliminating inequality, a potentially important EJ metric.

Quantitative HIA methods can enhance cumulative impact analyses, few of which have quantified health risks or impacts attributable to individual environmental hazards (Cushing et al. 2015). Most of these analyses have focused on assessing exposures to environmental hazards and identifying where minority or low income populations are affected, (e.g., Sadd et al. 2011; Su et al. 2009, 2012). As shown here and elsewhere, health burdens depend on many factors, e.g., exposures from an industrial facility are spatially varying, depending on distance, emissions, meteorology, population size and vulnerability. Variation at the intra-urban scale can be large, e.g., risks in a small fenceline community near an industrial complex in Texas were lower than in the rest of the city due to prevailing winds (Prochaska et al. 2014). Thus, hazard scores considering only the presence or proximity of hazards may inadequately represent the exposure potential and likely impacts.

Health and inequality metrics could strengthen accountability research, which examines the outcomes of regulatory and other policy decisions (Bell et al. 2011). For example, changes in community air pollutant levels have improved lung function among children living in Los Angeles, California (Gilliland et al. 2017); health and inequality metrics could show whether these benefits are equitably and effectively distributed.

Considerations for quantitative HIAs

Burden of disease and inequality results can be affected by the location of air pollution sources, dispersion characteristics, the location of vulnerable and susceptible populations, administrative boundaries, and the spatial resolution of the analysis. As examples, estimating the base case health impacts for SO_2 emissions estimated at the ZIP code level in Detroit tremendously smooths gradients in exposure and lowers AI values; including areas with a high degree of social advantage (e.g., non-Hispanic white populations) or excluding potentially vulnerable populations can change CI values and possibly the groups identified as disproportionately harmed (Table A4.1). Sensitivity analyses that vary the spatial scale and study boundaries can help evaluate the robustness of HIA findings.

Importantly, no standards or thresholds have been established for inequality assessments, and small changes in inequality metrics may not be meaningful. In general, alternatives that decrease inequality relative to the base case will be favored provided the decrease in inequality does not result from making better-off groups worse off. In the present application, changes in inequality resulted from decreases in health burdens since emissions were not allowed to increase. In other applications, health burdens may increase, and thus improvements in inequality must be coupled with an analysis showing how benefits are generated to ensure that no population subgroup is adversely impacted.

The inequality assessment, and in particular CI metric, is sensitive to the study boundaries. The study boundary used in this analysis includes the SO_2 non-attainment area and nearby cities which may have higher exposures and health burdens relative to other areas in southeast Michigan. Areas with potentially lower burdens are excluded, e.g., Oakland and Macomb counties, which are just north of the study area and have lower proportions of persons of color (26 and 18%, respectively) and persons living below the poverty line (10 and 13%, respectively) compared to the study area (68% persons of color and 31% persons in poverty) (US Census Bureau, 2014). Had these more affluent counties been included in the study area, the inequality metrics likely would have demonstrated disproportionate impacts among more disadvantaged groups, e.g., non-Hispanic Black residents in the study area, as seen elsewhere for social and environmental risks, e.g., living near hazardous land uses (Schulz et al. 2016). Rather than serve as a comparison between advantaged and disadvantaged communities, the results of this inequality analysis only allow decision makers to identify which population subgroups within the study area experience the highest burdens. This information can be useful in encouraging decision makers to act, e.g., to address an apparent environmental inequality, but should not be used as evidence of a lack of environmental justice issues for the broader Detroit region.

We did not consider costs or practicalities of pollution abatement. Costs will vary by source type, size, and many other facility-specific factors. Typically, smaller facilities incur greater costs per ton removed due to unavoidable fixed costs, e.g., capital and operational costs (Becker, 2005), and marginal costs usually increase at higher removal rates (Hartman et al. 1997). Based on abatement costs expressed as dollars per ton of pollutant removed, controls at large facilities may appear as more cost-effective, while reductions at smaller facilities may seem less economical. However, this accounting is incomplete: the lower per ton control costs at large facilities might yield lower health benefits, while the higher per ton costs at smaller facilities might be offset by greater health benefits. Many practical issues affect such assessments, e.g., the availability and ease of installing SO_2 controls. As noted in the SIP, installing end-of-pipe controls at some sources could require substantial retrofitting because these facilities predate the requirement for SO_2 removal technologies (MDEQ, 2016).

Limitations

The HIA applications have important limitations. First, incidence rates in Detroit were available at county to ZIP code scales, which limits the ability to capture spatial variability. Second, information on individual-level exposures was not used, which can bias health impact estimates when people live in one area and work or attend school in other areas (Baccini et al. 2015; Tchepel and Dias, 2011). Third, health impacts from secondary pollutants (e.g., sulfate particles formed from SO_2) were not considered. Such impacts (especially mortality) due to secondary $PM_{2.5}$ can far exceed those of SO_2 (US EPA, 2010a). However, secondary pollutant formation at the urban scale, which typically occurs at a regional scale and results in relatively homogeneous $PM_{2.5}$ concentrations at the intra-urban scale (Turner and Allen, 2008), may be modest. Fourth, sensitivity and uncertainty analyses were limited. Potentially important uncertainties include baseline incidence rates, dispersion modeling results, and the CRs (Mesa-Frias et al. 2013; O'Connell and Hurley, 2009). Uncertainty in the CR will likely have the largest influence on health impact estimates (Chart-asa and Gibson, 2015).

The inequality assessment is limited by the ability to identify all vulnerable populations in the area. The American Community Survey (ACS) data allows some analyses by race or Hispanic/Latino ethnicity. In Detroit, 90% of the population identifies as Hispanic/Latino or non-Hispanic Black (US Census Bureau, 2015). However, our study area also included the city of Dearborn, which is approximately 30% Arab or Arab-American (de la Cruz and Brittingham, 2003), ethnicity data not yet routinely collected by the US Census Bureau. Many Arab and Arab American residents experience high exposures to social stressors, e.g., discrimination (Padela and Heisler, 2010; Samari, 2016) and therefore would be an important subpopulation to include in EJ and CI analyses.

Conclusions

Air quality management (AQM) and control strategies can be improved by incorporating health and inequality metrics. The combination of spatially variable exposures and known inequalities in health status and vulnerable subpopulations motivates the use of spatially-resolved HIAs to assess health inequality as well as the health burden. In the study area, which includes Detroit, MI and contains a designated SO_2 non-attainment area, SO_2 continues to have a substantial impact on the health of the population, particularly among children and Hispanic or Latino populations. AQM strategies that focus on emission sources with the highest health impacts per ton of pollutant emitted provid the greatest health benefit per ton of pollutant reduced; these strategies also reduce the inequality of health risks. In contrast, strategies targeting the larger emitters increase inequalities and sometimes provid minimal health benefits. Assessments that incorporate HIA techniques and inequality metrics are feasible and allow AQM to move beyond compliance with ambient standards towards strategies that promote health and equity.

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Table 4.1. Descriptions of the SO_2 reduction strategies.

ID	Name	Emphasis	Description
S0	Base case		Base case of actual emissions based on averaged emissions reported in MAERS, 2010 to 2014
S1	Uniform percentage	Emissions	Applies uniform reductions across all major source facilities to meet tonnage reduction goals
S2	Largest emissions first	Emissions	First ranks facilities by total tons emitted and then applies controls to largest facilities first
S3	Health impact ranking	Health	Applies controls to facilities that have the largest health impacts per ton of SO_2 emitted first
S4	Receptor concentration optimization	Concentrations	Optimizes emissions at each facility to minimize receptor concentrations across the study domain
S5	Health impact optimization	Health	Optimizes emissions at each facility to minimize total health impacts across the study area
S6	SIP “maximum allowable” case		Base case of maximum allowable emissions used to develop the SIP control strategy. Used as comparison case for S7-S9.
S7	SIP control strategy	Emissions	Emissions reductions specified by the MDEQ SIP for SO_2 non-attainment. Includes the elevated stack at Carmeuse Lime.
S8	SIP receptor concentration optimization	Concentrations	Optimizes maximum allowable emissions at each facility to minimize receptor concentrations across the study domain
S9	SIP health impact optimization	Health	Optimizes maximum allowable emissions at each facility to minimize total health impacts across the study area

Table 4.2. Statistics of hourly SO_2 concentrations (ppb) at non-fenceline receptors, daily mean SO_2 concentrations (ppb) across all census blocks (used in health impact functions), and daily 1-hour maximum concentrations recorded at the Southwest High School monitor (2011-2015), which was shown to be out of attainment for the SO_2 NAAQS. Concentrations at receptors and blocks consider emissions from all point sources in the base case.

Metric	Min	25th	50th	Mean	75th	95th	99th	Max
Hourly at receptors	0	0.1	0.2	1.6	0.9	8.8	19.8	229.8
Daily mean across blocks	0	0.1	0.5	1.2	1.7	4.2	6.5	20.9
Daily 1-hr max at SWHS	0	1.7	4.6	12.4	16.0	52	71.8	111.6

Table 4.3. Annual health impacts (95% confidence interval)[1] for residents of Detroit and downriver cities attributable to baseline emissions of SO_2.

Outcome	Age Group	Attributable impacts per year
Asthma hospitalization (cases)	0- 64 years	7 (0 – 22)
COPD hospitalization (cases)	≥ 65 years	60 (0 – 120)
Asthma ED visit (cases)	0 – 17 years	95 (50 – 140)
Asthma ED visit, Detroit CR (cases)[2]	0 – 17 years	110 (50 – 170)
Asthma exacerbation (cases)[3]	6 – 14 years	6,100 (0 – 12,000)
Asthma exacerbation, Detroit CR (cases)[2,3]	6 – 14 Years	26,000 (6,000 – 46,000)
Total DALYs[4] (years)		7 (0 – 14)
Total monetized impact[4] (1,000's 2010$)		2,700 (0 – 5,500)

[1] Number of attributable cases to two significant figures. Confidence intervals (CI) estimated using the 95% CI of the CR coefficient. The lower bound of the 95% CI is truncated at zero.
[2] These estimates use a CR coefficient drawn from a study set in Detroit, MI.
[3] An asthma exacerbation is defined as a day with cough, wheeze, and/or shortness of breath.
[4] Total DALYs and monetized impact metrics exclude outcomes for which a Detroit-specific CR is used.
Abbreviations: COPD: Chronic obstructive pulmonary disease; CR: concentration-response coefficient; DALYs: disability-adjusted life years

Table 4.4. Base case (S0) average SO_2 emissions (2010 to 2014), attributable health impacts per year[1] among the total population, and attributable health impacts per 100 tons of SO_2 emitted per year for 9 major sources and 125 (aggregated) minor sources in the Detroit area.

Facility	Average Emissions (tons year^{-1}) (% of total)	Rank	Attributable DALYs (DALYs year^{-1}) (% of total)	Rank	Health impacts per 100 tons SO_2 emitted per year (DALYs tons^{-1} year^{-1})	Rank
Carmeuse Lime	640 (0.7)	8	0.40 (5.7)	7	0.062	1
Dearborn Industrial Generation	768 (0.8)	6	0.43 (6.2)	6	0.056	2
Severstal/AK Steel	733 (0.8)	7	0.38 (5.5)	8	0.052	3
Marathon Petroleum	268 (0.3)	9	0.13 (1.8)	9	0.047	4
US Steel Great Lakes Works	2,885 (3.1)	4	1.32 (18.9)	2	0.046	5
EES Coke	2,049 (2.2)	5	0.55 (7.9)	5	0.027	6
DTE River Rouge	10,442 (11.1)	3	0.80 (11.5)	4	0.008	7
DTE Trenton Channel	20,824 (22.2)	2	0.89 (12.7)	3	0.004	8
DTE Monroe	47,409 (50.6)	1	1.33 (19.1)	1	0.003	9
Minor point sources (n=125)	7713 (8.2)	NR	0.75 (10.7)	NR	0.010	NR
All point sources	93,731 (100)	NR	6.95 (100)	NR	0.007	NR

[1] Total health impact is estimated as DALYs. When several concentration response (CR) coefficients are available for an outcome, the more nationally-representative CR is used.
Abbreviations: DALYs: disability-adjusted life years; NR: not ranked

Table 4.5. Fourth highest 1-hour daily maximum SO_2 concentration (ppb) at non-fenceline receptors for each emissions control strategy and tonnage reduction goal.

Aggregate Reduction (%)	Uniform Percentage (S1)	Largest emissions first (S2)	Health impact ranking (S3)	Receptor concentration optimization (S4)	Health impact optimization (S5)
0%	79.5	79.5	79.5	79.5	79.5
15%	70.2	77.6	69.5	68.7	69.5
30%	60.7	75.7	69.4	62.3	69.4
45%	56.4	73.8	66.9	56.4	66.5
60%	56.3	61.9	56.3	56.3	56.3
75%	56.2	61.6	56.2	56.2	56.2
90%	56.2	56.2	56.2	56.2	56.2

Table 4.6. Total health burden (DALYs), Atkinson index and concentration index values (× 100) for annual health impact risk (measured as risk of a DALY per year) due to point source SO_2 emissions for each reduction strategy. Percent difference between the strategy and the base case in parentheses. Negative percent differences indicate an increase relative to base case.

				Concentration Index (× 100)						
Strategy	% Reduction	DALYs year^{-1}	Atkinson Index	Percent nonwhite	Percent Hispanic or Latino	Percent with less than a high school diploma	Median income (2014$)	Percent of households with income below poverty level	Percent of the population that is persons of color	Percent of the population that is foreign born
S0	0	7.0 (*)	0.136 (*)	7.8 (*)	-11.2 (*)	-8.9 (*)	-1.7 (*)	-4.8 (*)	6.1 (*)	-11.7 (*)
S1	15	6.2 (10.5)	0.134 (1.3)	7.7 (0.9)	-10.9 (2.3)	-8.6 (3.5)	-1.5 (9.6)	-4.6 (3.6)	6.1 (0.4)	-11.4 (1.9)
S1	30	5.5 (21.0)	0.132 (2.9)	7.6 (2.1)	-10.6 (5.3)	-8.2 (8.0)	-1.3 (21.8)	-4.4 (8.0)	6.0 (0.8)	-11.2 (4.3)
S1	45	4.8 (31.5)	0.129 (4.8)	7.5 (3.6)	-10.2 (9.2)	-7.7 (13.8)	-1.0 (37.7)	-4.1 (13.9)	6.0 (1.4)	-10.8 (7.4)
S1	60	4.0 (42.0)	0.126 (7.2)	7.4 (5.7)	-9.6 (14.6)	-6.9 (21.7)	-0.7 (59.3)	-3.7 (21.9)	5.9 (2.3)	-10.3 (11.6)
S1	75	3.3 (52.5)	0.122 (10.3)	7.1 (8.8)	-8.7 (22.3)	-5.9 (33.1)	-0.2 (90.6)	-3.2 (33.3)	5.9 (3.6)	-9.6 (17.7)
S1	90	2.6 (63.1)	0.117 (14)	6.7 (13.6)	-7.3 (34.4)	-4.3 (51.1)	0.7 (139.6)	-2.3 (51.3)	5.7 (5.6)	-8.5 (27.4)
S2	15	6.7 (3.5)	0.136 (-0.7)	7.6 (2.6)	-11.3 (-0.8)	-9.3 (-4.3)	-2.0 (-19.6)	-5.1 (-7.2)	5.8 (3.9)	-11.7 (-0.5)
S2	30	6.5 (7.1)	0.138 (-1.5)	7.4 (5.3)	-11.4 (-1.7)	-9.7 (-8.9)	-2.3 (-40.7)	-5.5 (-15.0)	5.6 (8.0)	-11.8 (-1.0)
S2	45	6.2 (10.6)	0.139 (-2.5)	7.2 (8.3)	-11.5 (-2.6)	-10.1 (-14)	-2.7 (-63.5)	-5.9 (-23.4)	5.3 (12.5)	-11.8 (-1.6)
S2	60	5.8 (16.3)	0.140 (-3.6)	7.3 (6.4)	-11.7 (-4.6)	-10.3 (-15.8)	-2.7 (-64.4)	-5.9 (-23.6)	5.4 (10.7)	-12.0 (-3.2)
S2	75	5.4 (22.7)	0.142 (-4.9)	7.6 (2.4)	-12.0 (-7.3)	-10.4 (-16.7)	-2.6 (-57.3)	-5.7 (-20.7)	5.7 (6.2)	-12.3 (-5.2)
S3	15	4.3 (38.2)	0.119 (12.0)	7.5 (4.4)	-8.2 (27.0)	-4.6 (48.4)	0.8 (145.8)	-2.2 (53.5)	6.4 (-4.7)	-9.2 (21.2)
S3	30	3.7 (46.8)	0.118 (12.6)	7.9 (-0.6)	-7.7 (31.1)	-3.5 (60.3)	1.6 (198.3)	-1.3 (72.9)	6.9 (-13)	-8.9 (24.0)
S3	45	3.3 (52.5)	0.119 (12.3)	8.2 (-5.1)	-7.7 (31.6)	-3.0 (66.1)	2.1 (228.3)	-0.8 (84.2)	7.2 (-19.3)	-8.8 (24.4)
S3	60	3.1 (56.0)	0.118 (12.8)	7.8 (0.1)	-7.6 (32.4)	-3.4 (61.9)	1.7 (203.5)	-1.2 (75.0)	6.8 (-12.4)	-8.7 (25.2)
S3	75	2.8 (59.5)	0.117 (13.4)	7.3 (6.3)	-7.5 (33.3)	-3.8 (57.0)	1.2 (174.4)	-1.7 (64.2)	6.3 (-4.2)	-8.6 (26.2)
S4	15	5.4 (22.1)	0.128 (5.7)	7.7 (1.7)	-9.8 (12.5)	-7.2 (18.3)	-0.7 (58.9)	-3.8 (20.7)	6.2 (-2.0)	-10.7 (8.0)
S4	30	5.1 (27.0)	0.128 (5.2)	7.7 (1.3)	-10.0 (10.8)	-7.4 (16.7)	-0.8 (54.2)	-3.8 (19.5)	6.2 (-2.1)	-10.8 (7.3)
S4	45	4.5 (35.6)	0.127 (6.6)	7.5 (4.0)	-9.5 (14.7)	-7.1 (20.0)	-0.7 (60.1)	-3.7 (21.2)	6.0 (0.4)	-10.5 (9.8)
S4	60	3.9 (44.0)	0.124 (8.6)	7.2 (7.4)	-9.0 (19.8)	-6.6 (25.5)	-0.5 (70.7)	-3.6 (24.9)	5.9 (3.1)	-10.1 (13.5)
S4	75	3.4 (51.6)	0.122 (9.9)	7.1 (9.6)	-8.5 (23.7)	-6.2 (30.4)	-0.3 (83.1)	-3.4 (29.5)	5.8 (4.7)	-9.7 (16.5)
S5	15	4.2 (39.7)	0.118 (12.7)	7.4 (5.4)	-7.8 (29.9)	-4.3 (51.9)	0.9 (156.2)	-2.0 (57.1)	6.3 (-4.4)	-8.9 (23.2)
S5	30	3.7 (47.0)	0.118 (12.7)	7.8 (-0.5)	-7.7 (31.5)	-3.5 (60.8)	1.6 (199.7)	-1.3 (73.4)	6.9 (-12.9)	-8.8 (24.2)
S5	45	3.3 (52.5)	0.119 (12.3)	8.2 (-5.0)	-7.6 (31.7)	-3.0 (66.0)	2.1 (227.9)	-0.8 (84.0)	7.2 (-19.2)	-8.8 (24.4)
S5	60	3.1 (56.1)	0.118 (12.9)	7.8 (0.3)	-7.6 (32.5)	-3.4 (61.7)	1.7 (202.6)	-1.2 (74.7)	6.8 (-12.1)	-8.7 (25.3)
S5	75	2.6 (62.8)	0.116 (14.7)	7.3 (6.2)	-6.7 (40.5)	-2.6 (70.7)	2.0 (219.4)	-0.9 (80.7)	6.5 (-7.0)	-8.0 (31.7)

Table 4.7. Summary statistics of block level daily mean and "peak" (4^{th} highest 1-hour daily maximum) concentrations (ppb) at non-fenceline receptors for the SIP maximum allowable case (S6), the SIP control strategy (S7), and the two optimized alternatives.

	Block-level daily mean concentrations at indicated percentile								
Strategy	Min	25^{th}	50^{th}	Mean	75^{th}	95^{th}	99^{th}	Max	Peak
SIP max. allowable (S6)	0	0.2	0.8	2.2	3.1	8.4	13.2	40.8	173.2
SIP control strategy (S7)	0	0.3	0.8	1.6	2.3	5.5	8.3	23.3	111.4
Concentration opt (S8)	0	0.2	0.7	1.6	2.5	6.1	9.1	24.5	106.7
Health opt (S9)	0	0.1	0.5	1.3	1.9	4.7	7.1	20.5	115.3

Table 4.8. Total health burden, Atkinson index (epsilon = 0.75), and concentration index values (× 100) for health impact risk (measured as risk of a DALY per year) for the SIP strategies. Percent difference between the strategy and the maximum allowable case (S6) in parentheses. Negative percent differences indicate an increase relative to base case.

			Concentration Index (× 100)						
Strategy	DALYs per year	Atkinson index	Percent nonwhite	Percent Hispanic or Latino	Percent with less than a high school diploma	Median income (2014$)	Percent of households with income below poverty level	Percent of the population that is persons of color	Percent of the population that is foreign born
S6	12.9 (*)	0.143 (*)	7.9 (*)	-12.0 (*)	-10.3 (*)	-2.5 (*)	-5.6 (*)	6.0 (*)	-12.5 (*)
S7	9.7 (24.5)	0.142 (1.0)	8.3 (-4.2)	-11.4 (4.9)	-10.0 (2.5)	-2.0 (19.9)	-5.2 (7.5)	6.4 (-5.9)	-12.6 (-0.6)
S8	9.8 (23.8)	0.142 (0.9)	8.1 (-2.5)	-11.7 (2.3)	-10.0 (2.5)	-2.1 (12.9)	-5.3 (5.4)	6.2 (-3.9)	-12.5 (-0.0)
S9	7.6 (40.6)	0.133 (7.3)	8.2 (-2.9)	-10.0 (17)	-8.0 (22.2)	-0.8 (66.5)	-4.0 (28.3)	6.6 (-9.7)	-11.6 (7.8)

* Percent difference relative to the base case S6.

Figure 4.1. Study area boundaries (blue outline), the SO_2 non-attainment area, and locations of major point sources of SO_2.

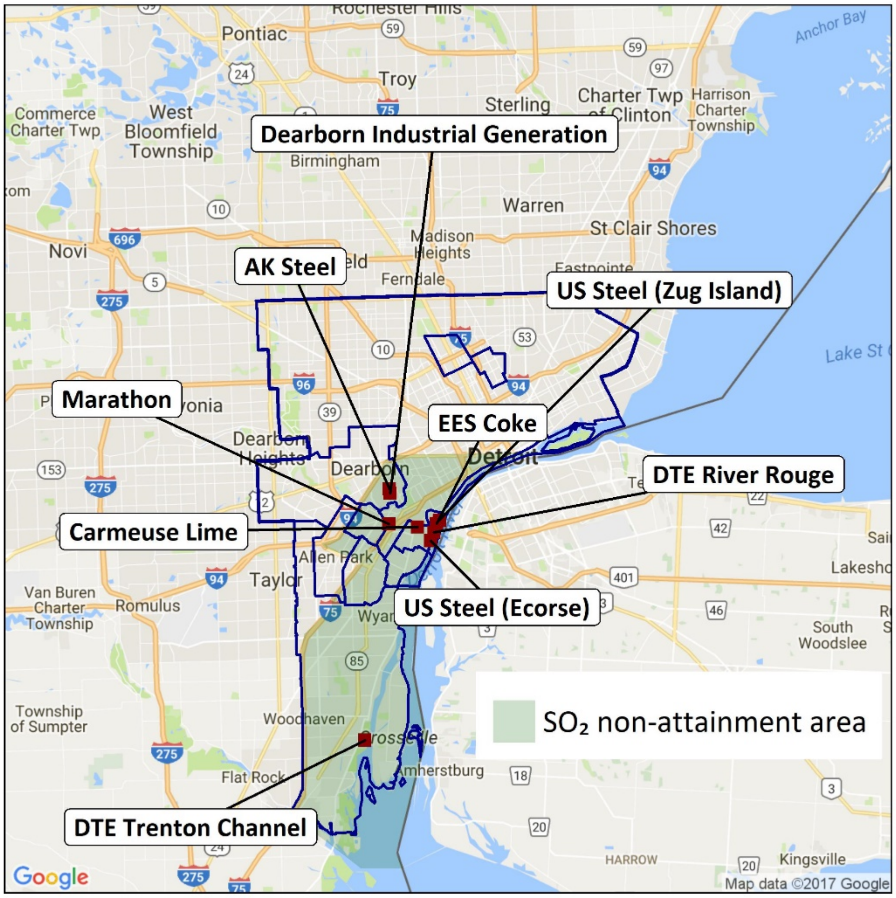


Figure 4.2. Annual average (A) and 4th highest 1-hour daily maximum (B) SO_2 concentrations (ppb) for the base case (S0). Based on 5-year average emissions of SO_2, 2012 meteorology, and all point sources. The blue line shows the HIA study area; the green dashed line shows the SO_2 non-attainment area.

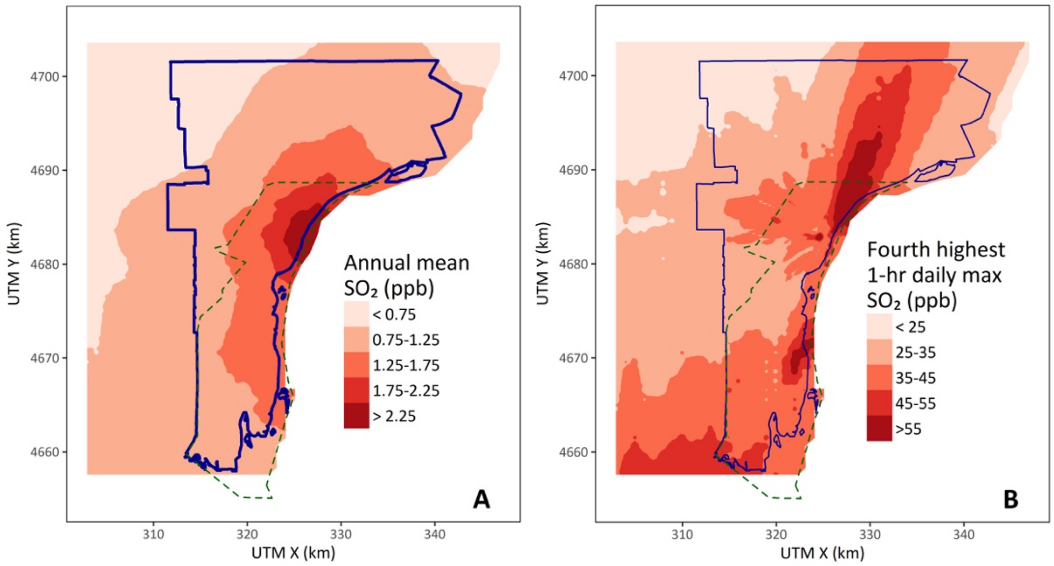


Figure 4.3. Attributable health burden (DALYs per year) versus Atkinson inequality index for each emission control alternative. Lines connect alternatives with the same SO_2 emissions reduction target (15 to 90%). AI inequality aversion parameter set to 0.75.

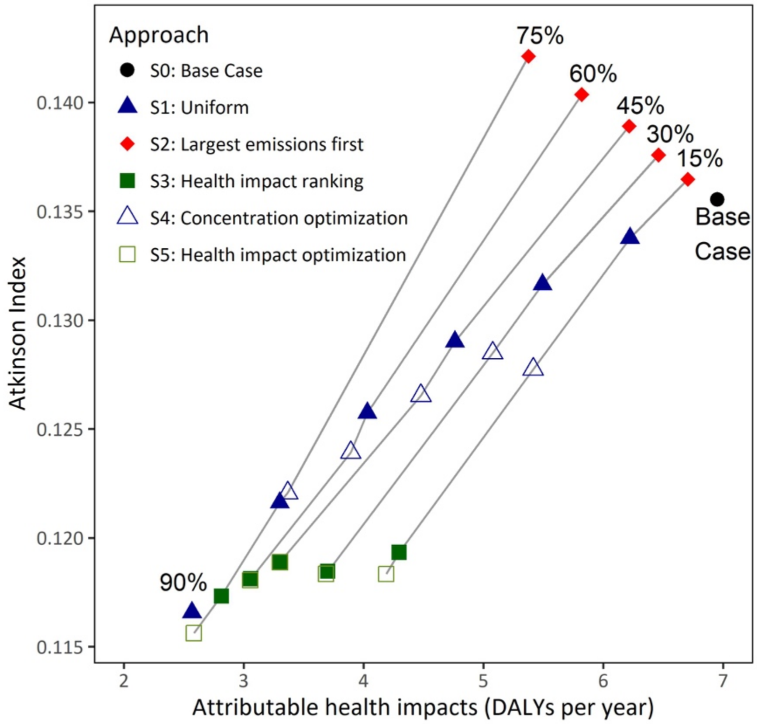
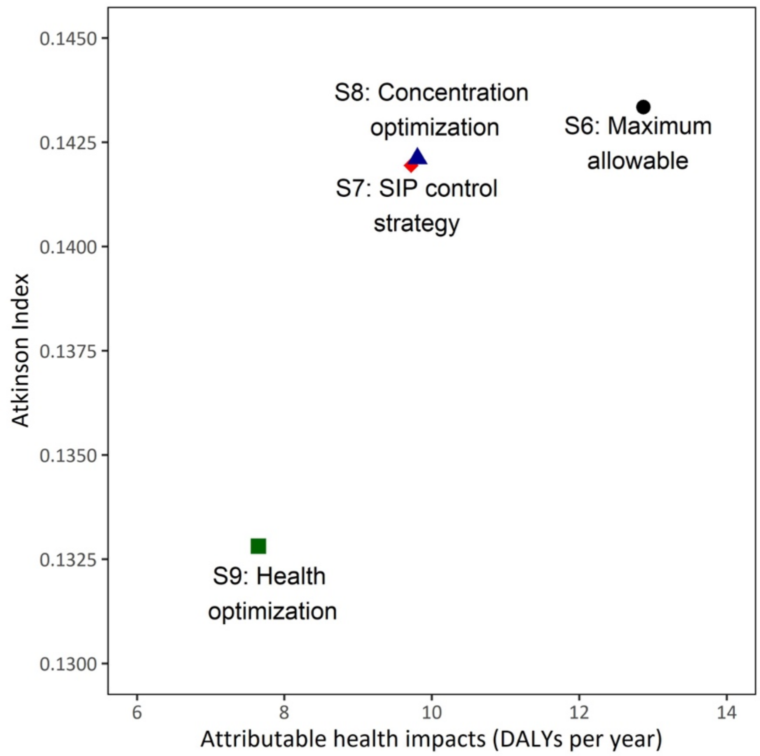


Figure 4.4. Attributable health burden (DALYs per year) versus Atkinson inequality Index (inequality aversion parameter = 0.75) for the SIP maximum allowable (S6), the SIP control (S7), and two optimized (S8 and S9) strategies.



Appendix A4

SUPPLEMENTAL MATERIALS FOR CHAPTER 4

Supplemental Tables

Table A4.1. Sensitivity analysis results for total health burden (DALYs), Atkinson index and concentration index values (× 100) for annual health impact risk (measured as risk of a DALY per year) due to point source SO_2 emissions in Detroit, MI and nearby downriver cities. Results are presented for the entire study area at the block level, the entire study area at the ZIP code level, and the subset of the census blocks that are within the non-attainment area (see Figure 4.1). Percent difference between the sensitivity analysis and the blocks-level analysis in parentheses.

			Concentration Index (× 100)						
Spatial Scale	DALYs per year	Atkinson index	Percent nonwhite	Percent Hispanic or Latino	Percent with less than a high school diploma	Median income (2014$)	Percentage of households with income below poverty level	Percentage of the population that is persons of color	Percentage of the population that is foreign born
Blocks	6.95	0.14	7.8	-11.2	-8.9	-1.7	-4.8	6.1	-11.7
ZIP	7.5	0.1	7.4	-13.1	-14.1	-2.4	-5.7	4.9	-10.9
Codes	(7.4)	(-137.6)	(-5.3)	(14.5)	(36.9)	(29.8)	(17.0)	(-23.8)	(-7.1)
NA zone	3.7	0.1	-10.3	-11.8	-12.8	-10.1	-12.2	-11.9	-10.2
blocks	(-88.4)	(-31.9)	(175.8)	(5.1)	(30.8)	(83.6)	(61.2)	(150.9)	(-13.9)

Supplemental Figures

Figure A4.1. Empirical cumulative distributions of the measured daily mean SO_2 concentrations at the Southwest High School monitor and predicted daily mean SO_2 at the four FRESH-EST receptors (R1, R2, R3, and R4) closest to the monitor (distance < 160 m.) K-S tests showed no statistically significant difference between the distributions of measured and predicted daily means ($p > 0.05$).

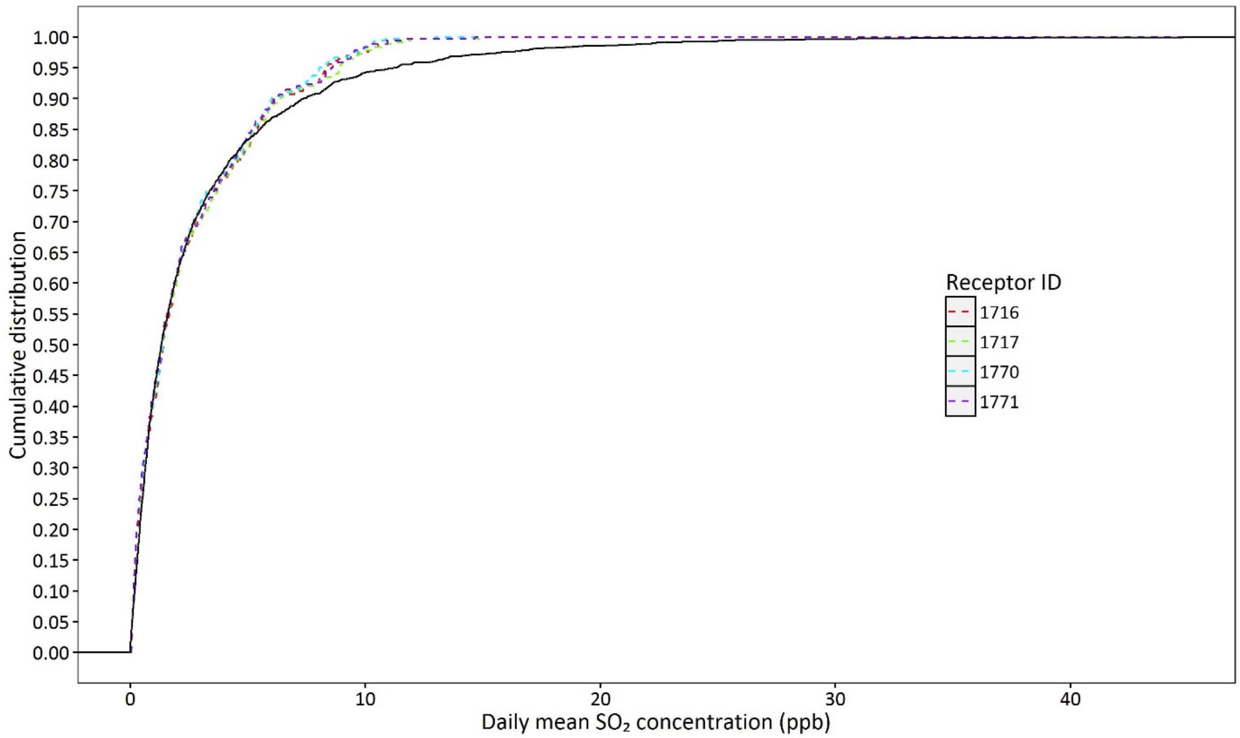


Figure A4.2A-G. Attributable health burden (DALYs per year) versus concentration index (CI) for each emission control alternative based on actual emissions and population subgroup. Lines connect alternatives with the same SO_2 emissions reduction target (15 to 90%). A CI equal to zero indicates perfect equality across census blocks. Negative CI values indicates the lower-ranked census block carries a disproportionate impact. Thus, alternatives that result in CI values closer to 0 are preferred.

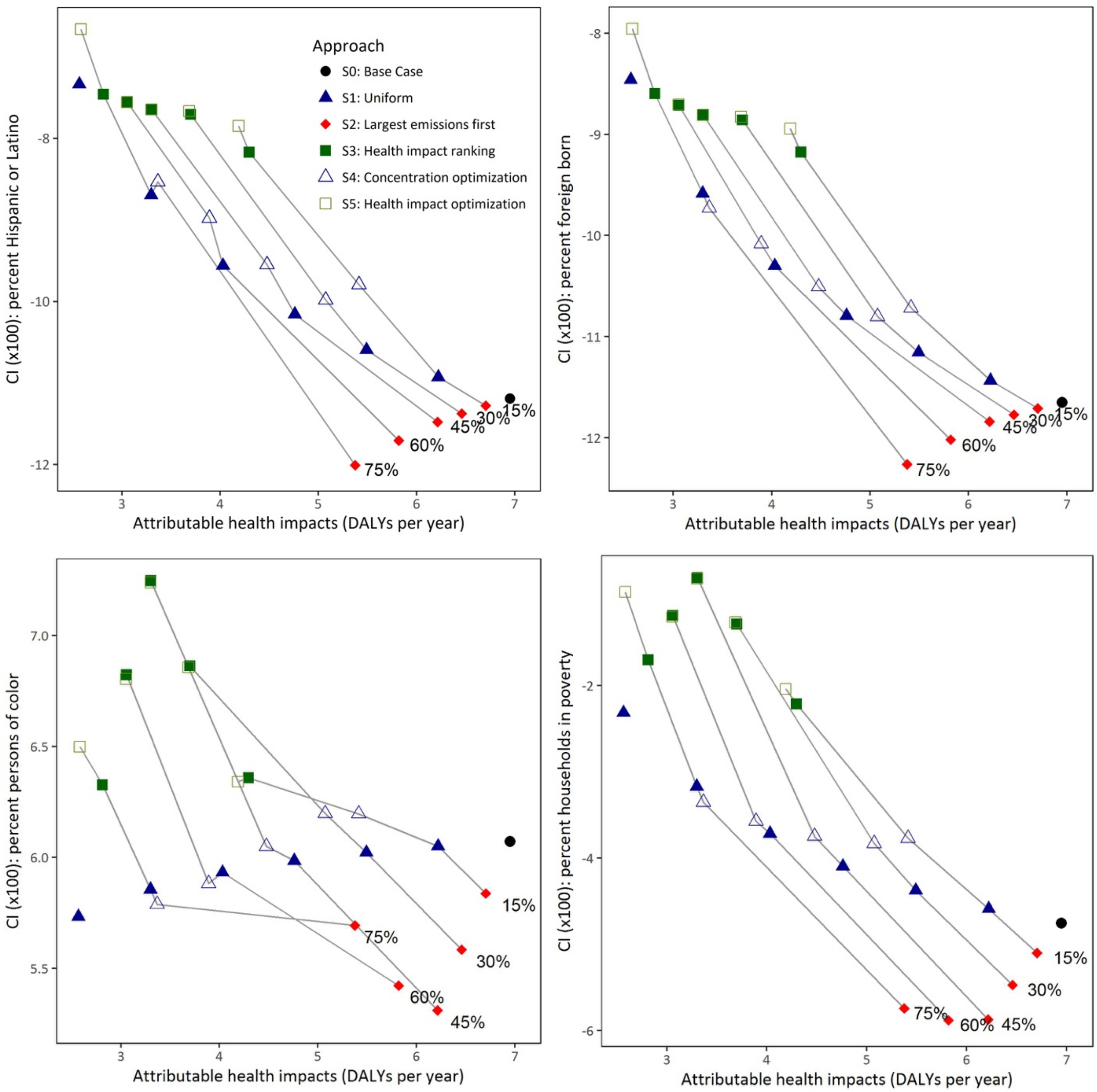


Figure A4.2A-G (continued). Attributable health burden (DALYs per year) versus concentration index (CI) for each emission control alternative based on actual emissions and population subgroup. Lines connect alternatives with the same SO_2 emissions reduction target (15 to 90%). A CI equal to zero indicates perfect equality across census blocks. Negative CI values indicates the lower-ranked census block carries a disproportionate impact. Thus, alternatives that result in CI values closer to 0 are preferred.

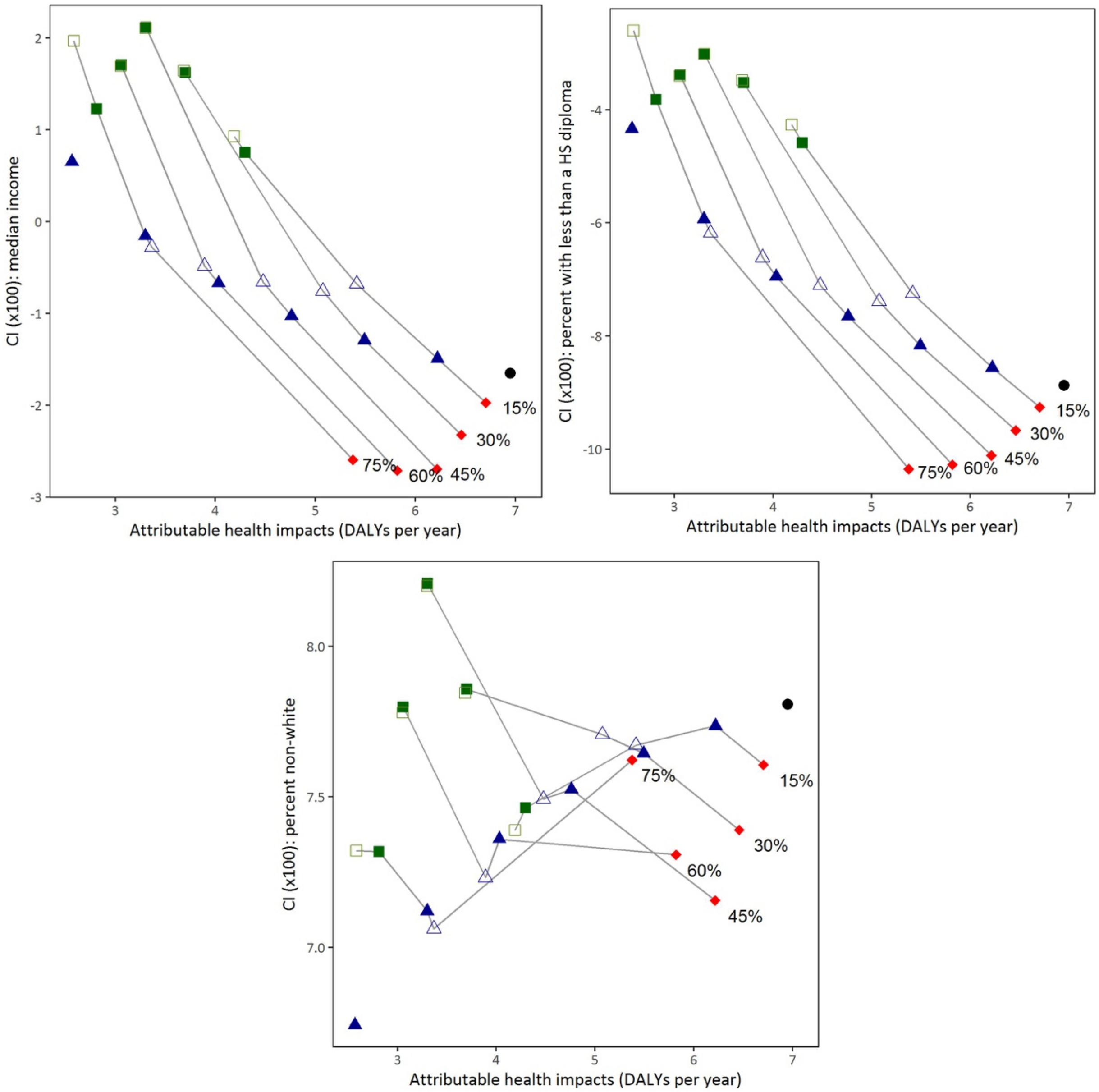


Figure A4.3A-G. Attributable health burden (DALYs per year) versus concentration index (CI) for each emission control alternative based on maximum allowable emissions and population subgroup. A CI equal to zero indicates perfect equality across census blocks. Negative CI values indicates the lower-ranked census block carries a disproportionate impact. Thus, alternatives that result in CI values closer to 0 are preferred.

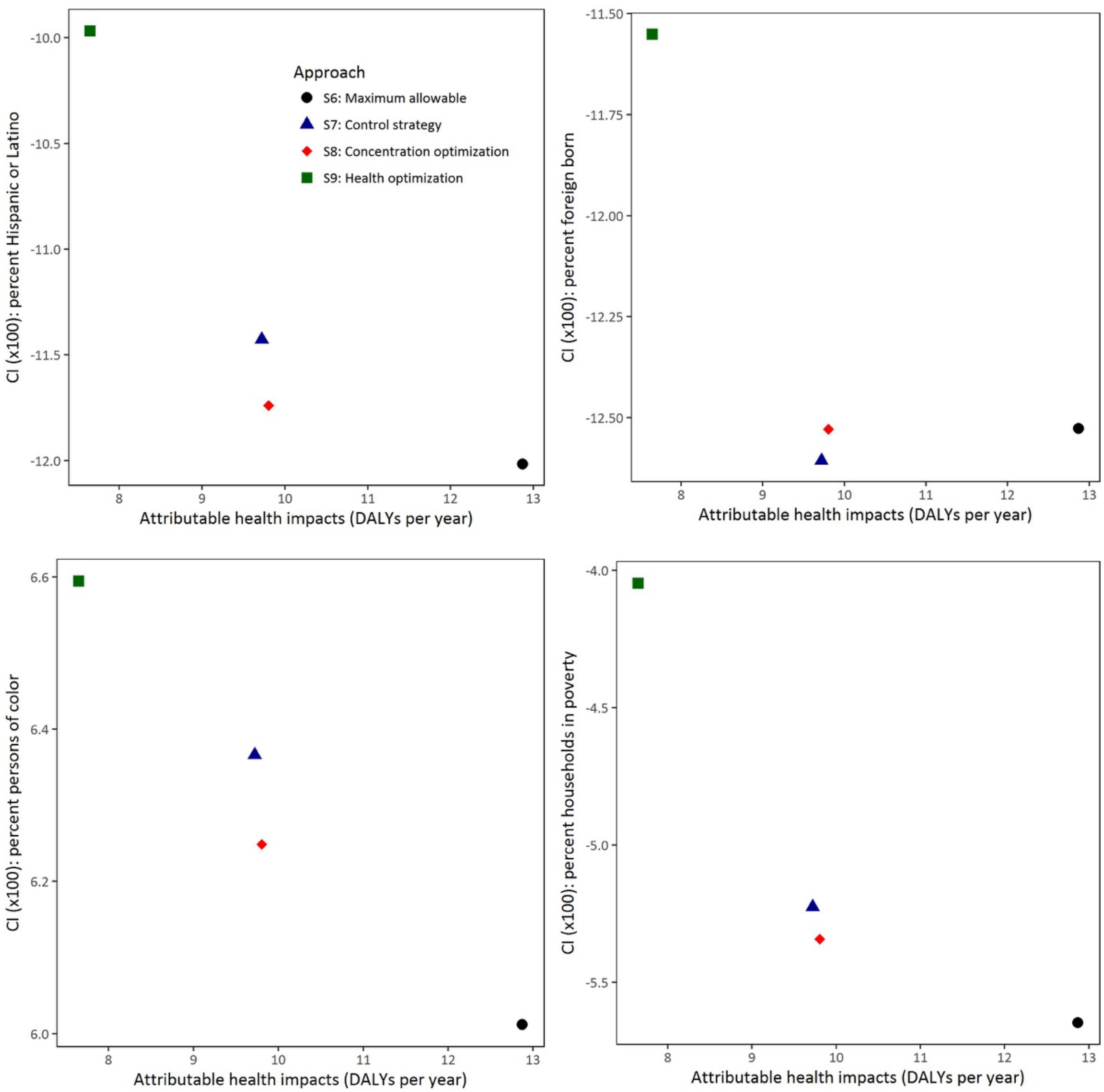
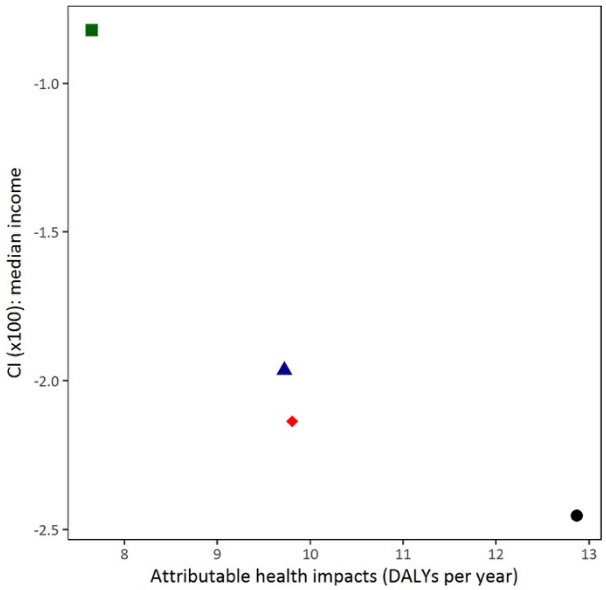
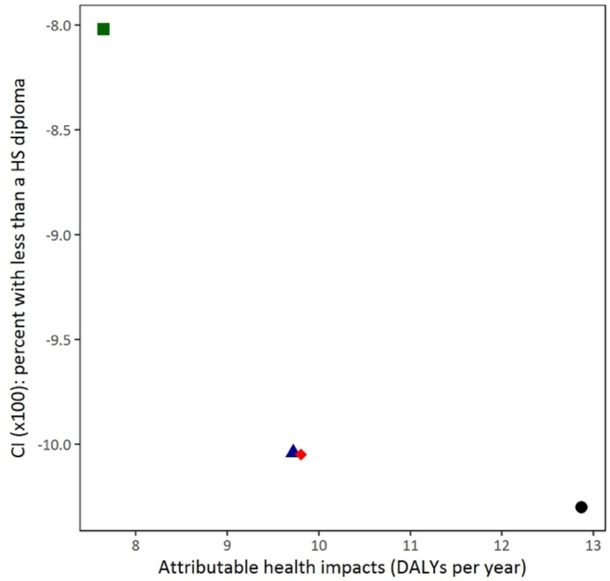
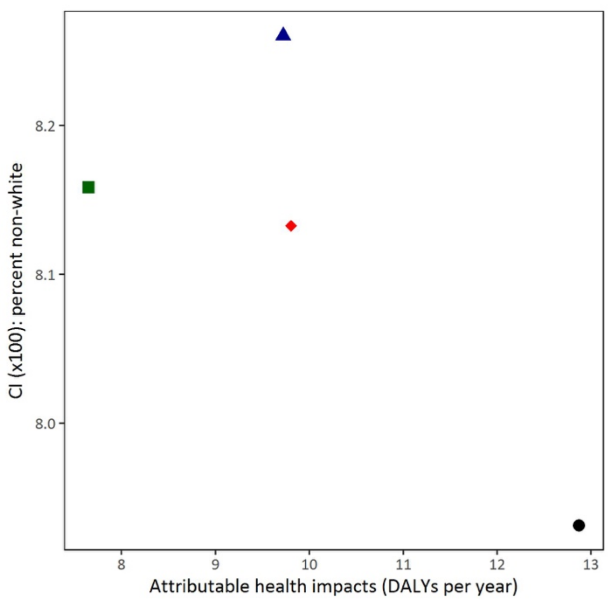


Figure A4.3A-G (Continued). Attributable health burden (DALYs per year) versus concentration index (CI) for each emission control alternative based on maximum allowable emissions and population subgroup. A CI equal to zero indicates perfect equality across census blocks. Negative CI values indicates the lower-ranked census block carries a disproportionate impact. Thus, alternatives that result in CI values closer to 0 are preferred.







Chapter 5

ASTHMA-RELATED HEALTH BENEFITS OF EFFICIENT FILTERS IN SCHOOLS AND HOMES

Abstract

Filters can reduce indoor concentrations of particulate matter ($PM_{2.5}$) in homes, schools, and other buildings, but their health benefits have not been well characterized. This study examines the health burden of asthma on school-age children associated with exposure to $PM_{2.5}$, and quantifies the benefits and costs of reducing exposures using filters at schools and residences. We examine schools and residences in and near Detroit, Michigan, estimate indoor $PM_{2.5}$ levels using indoor air quality models and ambient data, and evaluate the use of filters in forced air systems as well as free-standing filters. Health impact assessment (HIA) methods are used to quantify the impact attributable to $PM_{2.5}$ exposure and the benefit (as avoided impacts) of filters. The variability and uncertainty of model inputs are addressed using Monte Carlo analyses. Filters lower $PM_{2.5}$ concentrations from outdoor sources by 46 to 83% in schools, 34 to 56% in homes with forced air systems, and by up to 89% in rooms with free-standing HEPA filters. Replacing inefficient filters (MERV 5) with slightly better (MERV 8) filters in study area schools would avoid over 16,000 asthma symptom-days and 25 emergency department (ED) visits per school year, representing an 8% reduction in annual $PM_{2.5}$ attributable impacts (17%

reduction during the school year); MERV 12 and 14 filters increase annual reductions to 13 to 14%, respectively during the school year (28 and 30%, respectively during the school year). Widespread use of filters in schools confers monetized benefits of $1.0 to $1.8 million per year or $91 to $164 per child with asthma per year, compared to marginal costs $40 to $63 per classroom per year or $20 to $32 per child with asthma per year. In homes, using MERV 8 filters (and HEPA filters in homes without furnaces) results in 23,000 fewer asthma symptom-days and 33 fewer ED visits each year, an 11% reduction; MERV 12 and 14 filters increase reductions to 16%. The marginal cost in a home with a forced air system is $151 – 175 per house per year, mostly due to additional electricity to increase the duty cycle, and $494 per house per year for stand-alone filters. The cost of filters in homes is similar to asthma-related benefits ($118 to $182 per child with asthma per year). Filters can confer substantial health benefits with modest costs, providing a positive public health impact for school-age children.

Introduction

Children are susceptible to the adverse effects of ambient air pollution due to higher breathing rates, more time spent outdoors, and the sensitivity of their developing respiratory system (Gauderman et al. 2004; Goldizen et al. 2016; Rice et al. 2016; Wright and Brunst, 2013). Children with asthma are especially vulnerable, and exposure to air pollutants has been linked to reduced lung function, symptoms including cough, wheeze, and shortness of breath, and emergency department (ED) visits and hospitalizations (Li et al. 2011; Liu et al. 2009; Mar et al. 2010; Ostro et al. 2001; Samoli et al. 2011; Schildcrout et al. 2006). Air pollutant exposure may also contribute to new cases of asthma, especially among children living or attending school near busy roads (Gehring et al. 2010; McConnell, 2007; McConnell et al. 2010; Nishimura et al. 2013). Children with asthma may be more likely to miss school (Mizan et al. 2011; Moonie et al. 2010; Rodriguez et al. 2013), which may lead to lower academic achievement (Baxter et al. 2011; Moonie et al. 2008). The vulnerability of children suggests that interventions that reduce pollutant exposures during childhood could yield large benefits.

Enhanced filtration in homes and schools can reduce fine particulate matter (with an aerodynamic diameter less than 2.5 µm; $PM_{2.5}$) exposures that originate from both indoor and outdoor emission sources (Du et al. 2011; Fisk, 2013; McCarthy et al. 2013; Polidori et al. 2013). Children spend most of their time indoors at home (US EPA, 2011), and indoor PM concentrations can greatly exceed outdoor levels due to smoking, cooking, and PM resuspension from vacuuming and other activities (Chen and Zhao, 2011; Ferro et al. 2004). After homes, children spend most of their time in schools. $PM_{2.5}$ levels in schools are influenced by indoor and outdoor sources, including traffic (Amato et al. 2014; John et al. 2007). In both homes and schools, the building's envelope, heating, ventilation and air conditioning (HVAC) system, filters, and other factors affect indoor concentrations (Stephens, 2015).

Objective and motivation

This study estimates the exposure, health, and cost impacts of using high efficiency filters in homes and schools. We focus on the asthma-related health burden among school-aged children attributable to $PM_{2.5}$ exposure. Prior studies of filters have examined health impacts on adults, e.g., hospitalizations and premature mortality; benefits to children, a susceptible population, have not been well characterized (Fisk, 2013; Fisk and Chan, 2017; Logue et al. 2012; MacIntosh et al. 2010).

The setting for this study is Detroit, MI and nearby cities (Hamtramck, Highland Park, River Rouge, Ecorse, Melvindale, Lincoln Park, Dearborn, and Allen Park) located in Wayne County, Michigan. Many children in the study area are potentially vulnerable given their low socioeconomic status and high rates of poverty (e.g., 74% of students attending public schools in the study area are economically disadvantaged; MDE, 2016), high prevalence of asthma (11.3% in Detroit), high rates of asthma hospitalizations (nearly three times higher that of the state; MDHHS 2014), and the reliance on EDs for primary care (DeGuire et al. 2016). Furthermore, children in the area may experience major educational disparities, e.g., for public school students in the study area, daily attendance is only 89% (versus 93.4% in Michigan) and 7.4% score as "proficient" on state standardized tests (versus 18% of students statewide; MDE, 2016). The southeast Michigan region has many local $PM_{2.5}$ sources including industry, on-road mobile sources, non-road, and area sources that account for one-third to one-half of ambient $PM_{2.5}$ concentrations; the remainder arises from regional sources (Gildemeister et al. 2007; Milando et al. 2016). Wayne County contains 38 industrial facilities emitting over 1 ton per year of (primary) $PM_{2.5}$ (MDEQ, 2001), 23,000 miles of major roads, 4,000 miles of truck routes, five commercial marine ports, and seven rail and truck terminals (SEMCOG, 2013). Many highways cut through residential areas, and sections of several highways have over 10,000 trucks per day (MDOT, 2013).

Methods

Indoor $PM_{2.5}$ concentrations in classrooms and homes are estimated using indoor air quality models, a variety of filter types, and historical ambient $PM_{2.5}$ levels. Then, health impact functions are used to estimate health benefits as avoided morbidity. We focus on $PM_{2.5}$ from outdoor sources because the health impact functions were developed for ambient $PM_{2.5}$; in addition, indoor $PM_{2.5}$ sources vary greatly among buildings (and rooms within a building).

Study population

The study population is the nearly 136,000 children ages 6 to 18 years old attending the 290 schools in the study area (MDE, 2016). Enrollment in grades K through 8 is used to estimate the 6-14 year old population, and the total enrollment at the school is used to estimate the population under age 18. Of this population, 11,000 children are estimated to have asthma, based on the asthma prevalence for Detroit (11.3%; DeGuire et al. 2016). We assume children live and go to school in the same ZIP code.

Estimating $PM_{2.5}$ exposures at schools and homes

Indoor $PM_{2.5}$ levels arising from outdoor sources are estimated using steady-state models, which are amenable to uncertainty analyses, and local building characteristics (when available). Details are described below.

$PM_{2.5}$ concentrations in schools

$PM_{2.5}$ concentrations are estimated for a "typical" classroom using a unit ventilator (UV) that can accommodate a drop-in filter (Fisk et al. 2002). At steady-state, the indoor $PM_{2.5}$ concentration (C_s) due to outdoor sources is:

$$C_s = \frac{C_o\,[Q_{o,s}\,(1-\varepsilon_s) + Q_{in}P_s]}{Q_r\,\varepsilon_s + Q_{o,s} + Q_{in} + k_{dep,s}} \tag{5.1}$$

where C_o = outdoor $PM_{2.5}$ concentration ($\mu g\ m^{-3}$), $Q_{o,s}$ and Q_r = volume-normalized outside air and recirculation air flow rates, respectively, through the filter (h^{-1}), Q_{in} = volume-normalized infiltration air flow rate (h^{-1}), P_s = penetration factor for particles entering the classroom via air infiltration (dimensionless), $k_{dep,s}$ = particle loss rate due to deposition in classrooms (h^{-1}), and ε_s = particle removal efficiency of the filter (dimensionless).

Typical values of parameters in eq. (5.1) are shown in Table 5.1. The classroom air change rate (ACR) comes from a recent study of Midwestern schools that derived ACRs using CO_2 measurements and a transient mass balance simulation method (Batterman et al. 2017). This study also reports ACRs when the HVAC system is off, which are used for the infiltration rate Q_{in}. $Q_{o,s}$ (h^{-1}) is determined from the ACR and Q_{in} ($Q_{o,s}$ = ACR – Q_{in}). The recirculation flow rate Q_r comes from a U.S.-wide study on the benefits of ventilation and filtration in public buildings (Chan et al. 2016); we assume uncertainty of ± 1 h^{-1}. P_s is based on the predicted sulfate particle penetration for an office building with a low-efficiency (i.e., 6-8% removal) filter (Riley et al.

2002). Particle loss rate $k_{dep,s}$ is set to 0.10 h^{-1} (± 0.01 h^{-1}), the average found for urban particle size distributions (Riley et al. 2002).

We assume that the UV runs continuously during the school day. Most schools start ventilation systems early in the morning before students and staff arrive, and shut them at the end of the instructional period (Batterman et al. 2017). Indoor concentrations are assumed to reach steady-state before occupancy.

$PM_{2.5}$ concentrations in homes with forced-air systems

Approximately 85% of homes in the study area have forced-air systems (i.e., whole-house furnaces) that can be fitted with a “drop-in” style filter (Du et al. 2012). In these homes, air tends to be well-mixed when the HVAC system is operating, i.e., in heating, cooling, or “fan” mode (Nazaroff, 2004). As for schools, indoor concentrations in homes with forced air systems are estimated using a fully-mixed one compartment model (Fisk et al. 2002) (Figure 5.1A). At steady state, the indoor $PM_{2.5}$ concentration (C_h) due to outdoor sources is:

$$C_h = \frac{Q_{o,h} C_o P_h}{Q_{h,f}\,\varepsilon_f + Q_{h,o} + k_{dep,h}} \tag{5.2}$$

where $Q_{o,h}$, $Q_{h,f}$ and $Q_{h,o}$ = volume-normalized flows from the outside into the house, from the house into the forced-air system, and from the house to the outside (h^{-1}), respectively, C_o = outdoor concentration (μg m^{-3}), P_h = penetration factor (dimensionless) for homes, $k_{dep,h}$ = deposition loss rate (h^{-1}), and ε_f = filter removal efficiency (dimensionless).

We again assumed typical values for parameters in eq. (5.2) (Table 5.1). The average whole house volume (302 ± 104 m^3) and ACR are based on a walk-through survey of Detroit houses (Du et al. 2012). We assume an average heating capacity of 60,000 BTU (63,303 kJ) system, 130 CFM (221 m^3 h^{-1}) of air per 10,000 BTU (10,550 kJ), a typical penetration factor P_h and particle loss rate $k_{dep,h}$ for urban $PM_{2.5}$ size distributions and house ventilation rates (Riley et al. 2002), and a duty cycle of 0.33 (e.g., fan and filter operate 20 min h^{-1}, thus we lower the filter flow rate by 67%).

Most houses in the study area are over 50 years old (median year built = 1966) and infiltration rates are relatively high (average of 0.73 h^{-1}) due to less tight building envelopes and opened windows for natural ventilation (Du et al. 2012; US Census Bureau, 2013). As a comparison case, a newer (post-1990) and "tight" house with closed windows and continuous air conditioning is modeled where the ACR averages 0.26 (IQR: 0.15 – 0.43) h^{-1} (Persily et al. 2010), P_h = 0.44 ± 0.11, and $k_{dep,h}$ = 0.09 ± 0.01 (Riley et al. 2002).

Filter efficiencies ε_f for filters with MERV ratings of 5, 8, 12, and 14 are derived for representative filters exposed to 196 different outdoor particle size distributions measured in Europe and North America; $PM_{2.5}$ efficiencies were not overly sensitive to particle density or size distribution assumptions. (Azimi et al. 2014). We also use values for high efficiency particle arrestance (HEPA) filters and include a "no filter" case; final values are listed in Table 5.1.

$PM_{2.5}$ concentrations in homes without forced-air systems

Stand-alone filters can be used in homes with radiators or baseboard heating (Du et al. 2012). These filters, rated by their "clean air delivery rate," typically service air in one or several rooms, but not the entire building, thus a multi-zone model is required. We model stand-alone units equipped with a HEPA filter using a three-compartment steady-state model representing a bedroom, living room, and the remainder of the house (Figure 5.1B). Filters are placed where children spend most of their time, namely, the bedroom and living room. Initially, we assume that each house has two filter units running simultaneously in these rooms. Indoor concentrations of $PM_{2.5}$ in the bedroom (C_i), living room (C_k), and remainder of the house (C_j) from outdoor sources are:

$$C_i = \frac{C_o P_h Q_{o,i} + C_j Q_{i,j} + C_k Q_{i,k}}{Q_{i,o} + Q_{i,j} + Q_{i,k} + k_{dep,h} + Q_{i,f_1} \varepsilon_1} \tag{5.3}$$

$$C_j = \frac{C_o P_h Q_{j,o} + C_i Q_{i,j} + C_k Q_{k,j}}{Q_{j,o} + Q_{j,i} + Q_{j,k} + k_{dep,h}} \tag{5.4}$$

$$C_k = \frac{C_o P_h Q_{o,k} + C_i Q_{i,k} + C_j Q_{j,k}}{Q_{k,o} + Q_{k,i} + Q_{k,j} + k_{dep,h} + Q_{k,f_2} \varepsilon_2} \tag{5.5}$$

where ε_1 and ε_2 = removal efficiencies of filters in the bedroom and living room (dimensionless), respectively, $Q_{i,f1}$ and $Q_{k,f1}$ = volume-normalized flows through bedroom and living room filters (h^{-1}), respectively, $Q_{o,i}$, $Q_{o,j}$, $Q_{o,k}$, $Q_{i,j}$, $Q_{j,k}$, $Q_{j,I}$, $Q_{j,k}$, $Q_{k,i}$, $Q_{k,j}$, $Q_{i,o}$, $Q_{j,o}$, and $Q_{k,o}$ = volume-normalized flows (h^{-1}) between compartments, subscripts *i, j, k,* and *o* = bedroom, other spaces, living room, and outside, respectively, and other parameters are as in eq. (5.2). Eqs. (5.3-5.5) are coupled. Subscripts on the flows indicate transfers among compartments. Indoor exposures in houses with stand-alone filters (C_{fil}) is the time-weighted average of exposures in bedrooms, living rooms, and other parts of the house. Values for the parameters in eqs. (5.3-5.5) are shown in Table 5.1.

Parameters in eqs. (5.3-5.5) follow those presented earlier with several exceptions. Volumes of homes without forced-air systems are larger (average of 418 ± 101 m^3), although children's bedrooms are smaller (27 ± 7 m^3) (Du et al. 2012). We assume the living room (room *k*) makes up 25% of the remaining volume (42 m^3). ACRs, which vary by season, represent the sum of all air entering a space, e.g., $ACR_i = (Q_{o,i} + Q_{j,i} + Q_{k,i})/V_i$ (Du et al. 2012). Bedrooms are assigned the bedroom ACR (1.66 h^{-1} ± 1.50 h^{-1}) and living rooms the house ACR (0.73 h^{-1} ± 0.76 h^{-1}); the remainder (bedrooms, kitchen, etc.) uses the average of bedroom and house ACRs (1.20 h^{-1}). Du et al. (2012) reported inter-zonal flow ratios by season (e.g., $\alpha_{h,b} = Q_{h,b} / [Q_{h,b} + Q_{o,b}]$) in a two compartment model derived from tracer gas analyses; average ratios are given as $\alpha_{b,h}$ = 0.26 ± 0.20 and $\alpha_{h,b}$ = 0.55 ± 0.18, where subscripts b and h indicate the bedroom and the whole house, respectively (Du et al. 2012). The three compartment model requires inter-zonal flows between bedrooms and the two other compartments; we assume that flows are proportional to the volume of the receiving spaces, i.e., that 25% of flows leaving the bedroom go to the living room and 75% to other spaces, and that flow ratios between the living room and the remainder of the house ($\alpha_{k,j}$ and $\alpha_{k,j}$) are 0.25. Inter-zonal flows are determined using the ACR and inter-zonal flow ratio, e.g., $Q_{i,k} = ACR_i \times \alpha_{i,k}$. For each compartment, flow balance is maintained. Average flows between the three compartments are summarized in Table 5.2. Seasonal inter-zonal flows are shown in Appendix A5 (Table A5.1).

Parameters of the stand-alone filter are taken from two commercially available HEPA filters. The bedroom filter (HPA100, Honeywell International Inc.) is rated for rooms up to 155 ft^2 (14 m^2) with a CADR of 106 CFM (180 m^3 h^{-1}) for dust. The living room filter (HPA300, Honeywell International Inc.) is rated for rooms of 465 ft^2 (43 m^2) with a CADR of 320 CMF (544 m^3 h^{-1}). These ratings use the unit's maximum fan speed (CADR = maximum speed × ε; Zhang et al. 2011). Given an efficiency of 99.97% (HEPA filter), the volume-normalized flows are 6.6 and 5.6 h^{-1}, respectively, for the bedroom ($Q_{i,f1} = CADR_{f1} / V_i$) and living room ($Q_{k,f2} = CADR_{f2} / V_k$) units. We assume that both filter units operate continuously at maximum speed while the child is at home, which was shown to be the most frequent fan speed used in a prior field study (Batterman et al. 2013) and, again, that the time needed to reach steady-state conditions is negligible.

Ambient $PM_{2.5}$ concentrations

Outdoor $PM_{2.5}$ concentrations are based on every 3rd day 24-hour measurements at 12 area monitoring sites from 2011-2015 (US EPA, 2014a). A 5-year record is used to account for the variability of the measurements. Only days with measurements from six or more sites are used. $PM_{2.5}$ concentrations are apportioned into the "background" (or regional) component, defined as the second lowest daily measurement across the monitoring sites, and the "local increment," defined as the highest daily measurement (at any monitor) minus the daily background. To account for elevated $PM_{2.5}$ levels near major roads (from exhaust emissions, entrained dust, tire and brake wear), the 75 schools within 200 m of a limited access freeway or state highway are assigned the full local increment; other schools and all homes are assigned half of the increment. This approach is supported by emissions inventory data that show mobile sources account for approximately 50% of the $PM_{2.5}$ emissions in Wayne County (US EPA, 2016), and receptor modeling apportionments that show approximately 50% of $PM_{2.5}$ in the area is due to regional sources and 15 to 30% from diesel exhaust and other mobile sources (Milando et al. 2016).

Parameter variability concentrations and filter use patterns

The variability of input parameters, e.g., flows, penetration factors and deposition rates, is evaluated using Monte Carlo (MC) analysis, 10,000 simulations, and the @Risk software (Palisade Corporation). MC analyses are performed for each filter rating and each of the three applications (schools, homes with forced-air systems, and homes without forced air systems). Distributional assumptions for input parameters are shown in Table 5.1. If a supporting study did not specify a distribution, a triangular distribution was assumed. In all cases, airflow balance was maintained, i.e., the sum of flows into a compartment is equal to the sum of flows out of the compartment.

For schools, outdoor concentrations are drawn from the set of ambient $PM_{2.5}$ concentrations on school days (i.e., weekdays from September 1 to June 15). Positive correlations between Q_r,

Q_{in} and Q_o are assumed (Spearman R = 0.3) since infiltration rates in schools tend to be higher when HVAC systems are operating (Ng et al. 2013).

For homes, daily outdoor concentrations are drawn from the set of ambient $PM_{2.5}$ concentrations in each season. The ACR bounds are set at 0.1 and 6 h^{-1}. For the multi-zone house model (eqs. 3-5), bedroom and whole house ACRs are positively correlated (R = 0.2), ratios of flows between the bedroom and the rest of the house ($\alpha_{b,h}$ and $\alpha_{h,b}$) are positively correlated (R = 0.2), and ACRs and ratios of flows between rooms are negatively correlated (R = -0.3) (Du et al. 2012)

The MC analysis does not address variability in the operating schedule for the UVs, forced-air systems, and stand-alone filters. However, sensitivity analyses are used to evaluate filter use rates from 0 to 100%.

Health impact assessment

The frequency of three asthma related outcomes among children, namely, hospitalizations (ages 6 to 18), emergency department (ED) visits (ages 6-18), and respiratory symptom days, defined as a day with cough, wheeze, or shortness of breath (ages 6-14), are estimated using quantitative health impact assessment (HIA) methods (Martenies et al. 2015). The concentration-response (CR) functions are taken from epidemiological studies (Mar et al. 2010, 2004; Ostro et al. 2001; Sheppard, 2003) with no effect threshold, consistent with current US EPA conclusions regarding the lack of evidence of a population-level exposure threshold (US

EPA, 2009). Baseline hospitalization rates are calculated at the ZIP code level using data from the Michigan Inpatient Database and the 2013 American Community Survey (US Census Bureau, 2015). Baseline ED visit rates are estimated from Medicaid data at the ZIP code level for schools in Detroit and the county level for other schools (DeGuire et al. 2016; MDHHS, 2014). We assume ED visit rates for children on Medicaid apply to the entire study population. More than 90% of children in Detroit (who account for 68% of children in the study area) and more than 55% of children in Wayne County are covered by Medicaid insurance (Annie E. Casey Foundation, 2017).

The number of attributable cases is converted to disability-adjusted life years (DALYs) and monetized impacts in 2010$ (CDC, 2012; de Hollander et al. 1999; Murray, 1994; US EPA, 2012a). A 95% confidence interval (CI) around the mean impact is estimated using the 95% CI of the CR coefficient, which accounts for most of the uncertainty in health impact estimates (Chart-asa and Gibson, 2015).

Calculating health benefits of filters

Health benefits are estimated for three sets of scenarios installing: efficient filters in all schools; in only “near road” schools (located within 200 m of a major road); and in all homes. Each scenario compares MERV 8, 12, and 14 filters to a baseline case: schools use a UV with an inefficient (MERV 5) filter; homes with forced air systems used the same filter; and no filtration is used in homes without forced-air systems ($Q_{i,f1} = Q_{k,f2} = 0$). Because US EPA recommends a minimum MERV 8-rated filter in classrooms (US EPA, 2012b), we also estimate the benefits of filter using MERV 8 as the baseline filter in UVs (see Appendix A5). Health benefits are reported as the number of avoided cases of asthma morbidity, avoided DALYs, and avoided monetized impacts. Percent reductions are reported for the full year, i.e., we scale percent reductions in impacts at schools by 0.48 to reflect that students are only in school 177 days each year.

There are several challenges in using CRs from air pollution epidemiological studies in filter studies. First, filters affect only a portion of total exposure. On average, people spend 87% of their time indoors (Klepeis et al. 2001), thus, outdoor concentrations represent a proxy of the total (indoor and outdoor) exposures in epidemiological studies. Second, the portion of indoor exposures affected by filters in epidemiological and filter studies can vary. Third, the CR functions are functions of outdoor concentrations, not indoor concentration. For these reasons, we calculate an "equivalent concentration," which accounts for indoor and outdoor exposures and is comparable with available CR functions. Using a time-weighted average of concentrations over the day, the equivalent concentration, C_{eq}, is calculated as:

$$C_{eq} = C_{out}\left[\frac{(\sum_m F_{in,m}C_{in,F,m}) + F_{out}C_{out}}{(\sum_m F_{in,m}C_{in,B,m}) + F_{out}C_{out}}\right] = C_{out}\left[\frac{(\sum_m F_{in,m}\, R_{F,m}\, C_{out}) + F_{out}\, C_{out}}{(\sum_m F_{in,m}R_{B,m}\, C_{out}) + F_{out}\, C_{out}}\right] \tag{5.6}$$

where F_{in} and F_{out} = fraction of time spent indoors and outdoors; $C_{in,F}$ and $C_{in,B}$ = indoor concentrations with enhanced filters and baseline filters, respectively; subscript *m* refers to the indoor space, e.g., homes or schools; C_{out} = outdoor concentration; and $R_{F,m}$ and $R_{B,m}$ = indoor/outdoor concentration ratios for space *m* with enhanced and baseline filters, respectively. This formulation does not account for possible differences in breathing rates between compartments, but these are unlikely to substantially affect results.

In eq. (5.6), C_{eq} is equal to C_{out} if indoor and outdoor concentrations are the same ($C_{in} = C_{out}$) or if the individual spends all of their time outdoors. If indoor concentrations without a filter are the same as outdoor concentrations ($R_B = 1$) and the filter removes half of the $PM_{2.5}$ ($R_F = 0.5$), then with the time allocations discussed above ($F_{in} = 0.87$), $C_{eq} = 0.57 \times C_{out}$. Given the same situation but assuming an individual spends all of their time indoors ($F_{in} = 1$), then, $C_{eq} = 0.5 \times C_{out}$. This result is similar to setting $C_{eq} = C_{in} \times F_{in}$, as used in previous filter studies (Logue et al. 2012). These simplified cases demonstrate how eq. (5.6) accounts for the attenuation of indoor $PM_{2.5}$ levels and time-activity patterns. This approach does not assume or require linearity in the CR and is consistent with methods used for ambient pollutants.

C_{eq} is estimated separately for schools and homes with the assumption that filters are used only in schools or homes, but not both. Time allocations use nationally representative values: 7.0, 1.9, 14.4, and 0.7 h day^{-1} in schools, outdoors, home and elsewhere, respectively, during school days, and 0, 1.9, 14.4, and 7.7 h day^{-1}, respectively, on non-school days (NCQT, 2015; US EPA, 2011). For the multi-zone model, the time spent in bedrooms, living rooms and other spaces in 10.5, 2.6, and 1.3 h day^{-1}, respectively (US EPA, 2011; Table 16-15). For homes and schools without improved filters, the average I/O ratios calculated using eq. (5.2 and 5.1) are 0.58 and 0.64, respectively. Indoor concentrations in the "other spaces" are unknown. For simplicity, we assume these exposures are the same as those at unfiltered homes during the school year; for estimates of C_{eq} during the full year, these unknown exposures are similar to those at unfiltered schools. These assumptions are based on seasonal time-activity data that indicate time spent by children under 12 at home is fairly consistent across seasons and that time spent in school during the fall, winter, and spring is replaced by time spent in other homes and other spaces, e.g. stores, during the summer (US EPA 2011; Table 16-12)

The MC analysis generates 10,000 iterations of outdoor and indoor concentrations in school and homes. We estimate C_{eq} for each iteration, and then fit a distribution to the results. From this distribution, concentrations are drawn randomly to create representative years (177 days for school exposures; 365 days for home exposures).

Because the health benefits of filters depend on the amount of time children spend in filtered indoor environments, the sensitivity of health benefits is demonstrated using two limiting scenarios: no time outdoors and 6 h day^{-1} outdoors.

Cost analysis

Costs of more efficient filters for schools and homes with forced air systems are referenced to low efficiency MERV 5 filters. Filter costs, which differ by MERV rating and size, are based on quotes from local suppliers. Stand-alone filters include a one-time cost for the purchase of the unit. For the stand-alone filters, annualized costs are estimated assuming a lifetime of 8 years and discount rate of 7% per year. Increased electricity consumption from running UVs, whole-house furnace fans, or stand-alone units assumes, at baseline, duty cycles of 0.07, 0.1 and 0, respectively, for classroom UVs, forced-air systems and stand-alone filters (Table 5.3); the marginal consumption is estimated for a range of increased duty cycles. Maintenance, retrofits and any additional heating and cooling costs are excluded. The cost-relevant factors are summarized in Table 5.3.

Results

Outdoor PM2.5 concentrations and Indoor/outdoor ratios

Daily mean ambient $PM_{2.5}$ concentrations during the study period (2011-2015) average 9.8 μg m^{-3} and range from 0.7 to 34.2 μg m^{-3} (Table A5.2). Calendar year and school year distributions are similar, though school-day concentrations tend to be lower than all-year concentrations. The mean “local increment” concentration is approximately 50% of the mean “background” concentration. $PM_{2.5}$ levels vary by season, e.g., near-road $PM_{2.5}$ concentrations (background plus the local increment) during the spring, summer, fall and winter averaged 11.3, 13.4, 11.6, and 14.1 μg m^{-3}, respectively (Kruskal-Wallis K=18.03, $p < 0.001$); the non-near road $PM_{2.5}$ concentrations (background plus half the local increment) average 9.3, 11.4, 9.6, and 12.0 μg m^{-3}, respectively (K = 23.7, $p < 0.001$).

As expected, I/O ratios decrease with increasing filter efficiency (Table 5.4, Figure 5.2). All I/O ratios are below one because indoor sources are excluded. Little seasonal variability is shown for building and filter type, in part due to the overlap between seasonal ACRs (Table 5.1). In schools, I/O ratios for MERV 5 filters are similar to those estimated without filters (Figure 5.2). I/O ratios are lowered from MERV 5 levels by 46, 80, and 83% using MERV 8, 12, and 14 filters, respectively. Homes show comparable trends: MERV 5 filters had little impact, and I/O ratio reductions were 34, 54, and 56% using MERV 8, 12, and 14 filters, respectively. Greater reductions in schools result from their lower ACR, in part due to their tighter building envelopes (Table 5.1), and higher initial I/O ratios at baseline relative to homes (Figure 5.3).

The two HEPA filters in homes without forced-air systems reduce I/O ratios by 84 and 88 in bedrooms and living rooms, respectively, relative to the baseline case (no filter; Table 5.4). The flows between the three-compartments obtain modest reductions (32%) in other parts of the home.

I/O ratios decrease as the filter duty cycle increases with the exception of classrooms equipped with MERV 5 filters (Figure 5.3A). In mechanically-ventilated classrooms, increasing the UV duty cycle time brings in more outside air, which increases $PM_{2.5}$ levels using inefficient filters. In contrast, in naturally-ventilated homes, increasing the fan duty cycle does not alter outside air flows, thus, increased filter use reduces the I/O ratio.

I/O ratios displayed in Figure 5.3B represent a typical home in Detroit, which is relatively "leaky." Without filters, the Detroit homes show considerably higher I/O ratios (0.59) than the "tight" homes (0.35; Figure A5.1), which have low ACRs and low $PM_{2.5}$ penetration factors. As the filter duty cycle increases, differences between these home types diminish, e.g., I/O ratios using a MERV 12 filter with a 90% duty cycle average 0.14 and 0.05 for "Detroit" and "tight" homes, respectively (Figure 5.3B, Figure A5.1). Thus, even leaky homes can attain low I/O ratios using efficient filters and high duty cycles.

Sources of variability shown by tornado plots for schools and homes with MERV 8 filters and for homes using stand-alone HEPA filters indicate that most variability in indoor $PM_{2.5}$ levels arises from the temporal variability of outdoor concentrations (Figure 5.4). (Plots for other MERV ratings are in the SI). Additional variability arises from ACRs, penetration factors, particle deposition rates, and filter efficiencies.

Health impacts

Health impacts from $PM_{2.5}$ exposure during the school year and calendar year, along with the estimated incidence of asthma-related impacts for the study population, are shown in Table 5.5. $PM_{2.5}$ exposures during the school year, for example, cause 83,000 asthma symptom-days defined as having cough and $PM_{2.5}$ exposures over the full year cause 170,000 days with cough; this can be compared to 1,400,00 days with cough due to all causes. In total, $PM_{2.5}$ exposures are responsible for an estimated 220 DALYs and $12.2 million in monetized impacts per year among school-aged children in the study area (Table 5.5). The annual results are similar to estimates presented previously based on ambient concentrations (270 DALYs per year; Chapter 3 Table 3.2). These baseline estimates of health impacts are not sensitive to the time children spend outdoors, e.g., attributable DALYs per year vary by less than 1% for outdoor durations from 0 to 6 h/day (Table A5.3, Table A5.4).

Benefits of filters

More efficient filters in classrooms and homes reduce the asthma-related health burden, mostly due to avoided asthma symptom days, i.e., days with cough, wheeze, or shortness of breath (Table 5.6). Replacing MERV 5 filters with MERV 8, 12, or 14 filters in schools reduces the annual $PM_{2.5}$-related asthma burden by 8, 13, and 14%, respectively (17, 28, and 30%, respectively, during the school year) which represents between $1.0 and $1.8 million per year in avoided health impacts. The marginal benefit of MERV 14 compared to MERV 12 filters is low (31 vs. 33 DALYs avoided per year, respectively). Benefits increase at near-road schools where annual DALYs are reduced by 10 – 17% (20 - 35% during the school year) compared to all schools (8 to 14% reduction), a result of the greater exposure (18% higher) at near-road schools. Benefits of filters in schools are somewhat sensitive to the time spent outdoors. If children spend no time outdoors (and are home an additional 1.9 h day^{-1}), benefits increase 6 to 7% (Table A5.5). If children spend 6 h day^{-1} outdoors (and 6 h day^{-1} less at home), benefits decrease by 10 to 12% (Table A5.6). Percent reductions in annual health burdens using MERV 12 and MERV 14 filters are lower when using MERV 8 filters at baseline (6 and 7%, respectively; Table A5.8) due to lower initial indoor concentrations under the MERV 8 baseline (Table 5.4).

At homes, filters avoid 24 to 36 DALYs per year, with monetized benefits from 1.3 to 2.0 million dollars per year, which exceed benefits at schools because children spend more time at home (Table 5.6). Replacing MERV 5 filters with MERV 8, 12, or 14 filters in homes reduces annual the $PM_{2.5}$-related asthma burden by 11, 16, and 16%, respectively (Table 5.6). As at schools, MERV 14 filters have only small benefits over MERV 12 filters. Again, results are somewhat sensitive to the time children spend outdoors. If children spend no time outdoors (and are home an additional 1.9 h day^{-1}), benefits increase by 6 to 8% (Table A5.5). If children spend 6 h day^{-1} outdoors (and 6 h day^{-1} less at home), benefits decrease by 8 to 9% (Table A5.6).

Filter-related costs and cost-effectiveness

Marginal costs depend on the filter rating and duty cycle (Table 5.7). In schools, replacing MERV 5 filters using a duty cycle of 0.07 with more efficient filters using a 0.20 duty cycle (177 days per year in each case) imposes marginal costs of $40 to $63 per classroom per year, depending on filter rating. With 20 students in a classroom (and 2 students with asthma per classroom), the marginal cost is $2 to $3 per student per year or $20 to $32 per student with asthma per year. This is well below the benefits of avoided asthma exacerbations ($1.0 to $1.7 million per year or $91 to $155 per child with asthma per year).

In a home with a forced air system, replacing MERV 5 filters using a duty cycle of 0.1 with more efficient filters and using a duty cycle of 0.3 costs about $151 to 175 per year, including increased energy costs of $142 per year. A home requiring two stand-alone filters using a 0.6 duty cycle incurs costs of $877 for the first year and subsequently $417 per year, or annualized costs of $494 per year. Because duty cycles over 50% provide only incremental benefits (Figure 5.3C), a lower duty cycle can obtain similar benefits with lower costs. For example, running stand-alone units 7.2 hours per day (0.3 duty cycle) has annualized costs of $432 per year. The total cost of more efficient filters in homes of children with asthma (assuming only one child with asthma in each home) is $2.2 - $2.4 million per year ($1.4 - 1.6 million per year for the approximately 9,350 homes with forced air systems and $800,000 per year for the 1,650 homes using stand-alone filters). Overall, filter costs in homes are similar to the monetized benefits estimated for avoided asthma impacts ($1.3 -2.0 million per year or $118 - 182 per child with asthma per year).

Discussion

The use of more efficient filters in schools and homes to reduce exposure of ambient $PM_{2.5}$ has significant benefits. Filters installed in schools can reduce the annual $PM_{2.5}$-related asthma burdens by 8 to 14%, depending on filter rating. Prioritizing schools near major roads and other sources of $PM_{2.5}$ emissions can help address environmental inequalities. The marginal costs of filters in schools is low, e.g., 20-32 per student with asthma per year, while benefits from avoided asthma exacerbations range from $91-163 per child with asthma per year.

More efficient filters installed in homes can lower the annual $PM_{2.5}$-related asthma burdens by 11 to 16%, however, this requires a filter in each home of a child with asthma. Marginal costs range from $151 to $175 per year for homes with forced air systems, and $494 per year for homes using two stand-alone filters. Benefits from avoided asthma impacts range from $1.3 to $2 million per year or $118 to $182 per child with asthma per year. These costs are similar to the monetized asthma-related health benefits. However, the true benefits of filters are likely higher given that filters also remove other asthma triggers, e.g., pet dander (Brown et al. 2014)(Brown et al. 2014), and adults are also susceptible to adverse health effects from $PM_{2.5}$ exposures.

Estimating the benefits of using filters in schools and homes simultaneously is beyond the present scope. This would be somewhat less than the sum of benefits of filters in both spaces (Table 5.6) due to the non-linear concentration-response coefficients, the variability in baseline exposures for different filter scenarios, and potentially other factors.

Indoor/outdoor ratios for schools and homes with filters

Several field studies have measured I/O ratios of $PM_{2.5}$ in schools that help to confirm our results (McCarthy et al. 2013; Polidori et al. 2013; Scheepers et al. 2012; van der Zee et al. 2016). For example, I/O ratios for black carbon (BC), which has few if any indoor sources in schools, ranged from 0.24-0.59 for classrooms using MERV 6 filters (McCarthy et al. 2013). We estimated comparable I/O ratios for $PM_{2.5}$, e.g., 0.86 and 0.46 for MERV 5 and 8 filters, respectively. I/O ratios of 0.03 - 0.26 have been estimated for MERV 15 filters (McCarthy et al. 2013), similar to our estimate of 0.15 for MERV 14 filters. Higher I/O ratios (0.48 - 0.51) for BC have been measured in a classroom with a MERV 14 filter; high infiltration rates may have affected these results (van der Zee et al. 2016). Differences between the literature and our results can result from differences in building characteristics, UV duty cycles, particle size distributions (Riley et al. 2002; Sarnat et al. 2006), and other factors.

We demonstrate the sensitivity of I/O ratios to the filter duty cycle, and show that without proper filtration, increasing the duty cycle of a classroom UV can increase I/O ratios due to increased amounts of poorly filtered outside air (Figure 5.3). Many classrooms need additional ventilation to lower levels of indoor contaminants and improve student and teacher health (e.g., Batterman et al. 2017; Chan et al. 2016; Kinshella et al. 2001; Mendell et al. 2013; Muscatiello et al. 2015). However, additional outside air should be provided using efficient filters that can avoid potential increases in concentrations of outdoor contaminants.

Our results apply to schools using UVs, a simple and low-cost HVAC system used in many schools. Schools use many other types of mechanical ventilation systems, e.g., central air handling units with variable air volume systems, but most systems blend outside air with recirculated air. These systems also use a variety of filters. While assessment of filter cost and performance for these systems is beyond the present scope, the use of more efficient filters likely has relatively low marginal costs, potentially similar to those estimated for UVs.

Our estimates of I/O ratios in homes with forced-air systems (Table 5.4, Figure 5.3) show reasonable agreement with prior field and modeling studies. Using a mass balance model, Azimi et al. (2016) estimated I/O ratios for older homes of 0.40, 0.32, 0.25, and 0.25 MERV 5, MERV 8, MERV 12, and MERV 14 filters, respectively, which are similar to our estimates of I/O ratios in homes with forced air systems (0.56, 0.37, 0.25, and 0.24 for MERV 5, MERV 8, MERV 12, and MERV 14, respectively; Table 5.4). Measured I/O ratios of $PM_{2.5}$ in homes vary geographically, e.g., 0.68 to 0.81 for homes in Detroit (Logue et al. 2015); 0.55 for homes in North Carolina (Wallace and Williams, 2005); and 0.47 to 0.82 (average = 0.62) for homes across the US (Allen et al. 2012). Again, differences across studies are likely due to building characteristics, meteorological factors such as wind speed and indoor-outdoor temperature differences, use of air conditioning, and opening windows to ventilate homes (Stephens, 2015).

Stand-alone HEPA filters placed in bedrooms in Detroit homes achieved 50 to 77% reductions in indoor PM levels, with higher reductions for fine PM (aerodynamic diameter 0.3 – 1 μm; Batterman et al. 2012). Other studies using stand-alone filters have measured $PM_{2.5}$ reductions between 37 and 43% (Cheng et al. 2016; Kajbafzadeh et al. 2015; Park et al. 2017). Using the three-compartment model, we estimate that two stand-alone filters would remove 84% of outdoor $PM_{2.5}$ in bedrooms on average when run continuously and 77% when run 60% of the time (Figure 5.3). The higher reductions in the present analysis likely result from four factors: we assume filters are used 100% of the time children are home compared to 63% to 83% in the field studies; we assume filters were running at their maximum speed; we assume each home had an additional filter (placed in the living room) that would boost removals; and the field study measurements included PM from both indoor and outdoor sources, which would diminish the apparent reductions. When the filter in the living room is removed and filter in bedrooms is run at half speed for 60% of the time (a scenario similar to reported use patterns; Batterman et al. 2013), I/O ratios are reduced by 55% on average in bedrooms. Thus, our estimates of PM reductions and health benefits for the 15% of homes without forced-air systems may be overestimated.

Health benefits of filters

Only a few studies have examined the health benefits of increased filter use in any building type, including schools and homes (Fisk, 2013). Upgrading from MERV 7 to MERV 15 filters in schools across the US has been estimated to reduce attributable cases of mortality, chronic bronchitis and stroke risks by 33% (Chan et al. 2016). We report a similar percentage decrease for asthma-related outcomes using MERV 12/MERV 14 filters in Detroit-area schools, e.g., a 28-30% reduction for children relative to MERV 5 filters during the school year (13-14% during the year). US EPA's *Tools for Schools,* a guide for improving indoor air quality in K-12 schools, recommends filters with MERV ratings between 8 and 13 (US EPA, 2012b). However, less than half of school districts in the US have an indoor air quality policy in place (CDC, 2015). Our findings suggest using filters in schools could potentially confer health benefits to school occupants, including students, teachers, and staff, particularly when schools do not have existing filter programs

We also estimate between 11 and 16% reductions in annual $PM_{2.5}$-related asthma burden if every home with a child with asthma in the study area used more efficient filters (Table 6). A prior study including asthma outcomes for children estimated using high-efficiency electrostatic cleaners in home forced-air systems would reduce asthma exacerbation risk by 7.4% (MacIntosh et al. 2010). Our higher estimates may be attributable to the high baseline risk of asthma outcomes among study area children (DeGuire et al. 2016). Other studies of health benefits of filters have focused on outcomes relevant to adults, e.g., hospitalizations and premature mortality (Fisk, 2013; Fisk and Chan, 2017; Logue et al. 2012; MacIntosh et al. 2010).

Cost and cost-effectiveness

Overall filtration costs include the filter media itself, labor for filter change-out, and electricity for fan operation. Costs tend to increase with filter efficiency and use (Table 5.7). Because the highest rated filters (MERV 14, 16) achieved only slightly higher performance than lower rated filters (e.g., MERV 12; Azimi et al. 2016), less expensive intermediate-rated filters could still gain substantial health benefits. Filter costs fall on school districts, homeowners, landlords, and tenants, many of whom may be sensitive to costs. We also recognize that filter change-out may be less frequent than recommended, that high efficiency filters require regular replacement, that some HVAC systems operate without any filters, and that costs will vary depending on HVAC configurations.

Filtration costs will vary by geographical area due to differences in the price of electricity, the baseline duty cycle of the HVAC systems, and building configurations and parameters (e.g., ACR). For example, Detroit-area homes at baseline (no filter) have a duty cycle of 0.1 (air conditioning is atypical); increasing the duty cycle to 0.2 imposes a marginal cost of $71 - 103 per year (Table 5.7). In comparison, in Texas homes, the baseline duty cycle is higher (0.2) due to heavy air conditioning use (Cetin and Novoselac, 2015) and the electricity cost is lower ($0.11 per kWh; UEIA, 2017b), thus the marginal cost of filters (for the same duty cycle as in the study area) is only $9 -32 per year, essentially the cost increment of higher efficiency filter alone. Marginal costs can be higher in states like California, where baseline duty cycles are likely low (fewer heating and cooling days; EIA, 2017a) and electricity cost is higher ($0.19 per kWh), and moving from a 0.05 duty cycle to 0.20 incurs marginal costs of $132 – 165 per year. Still, in homes with children with asthma, filtration costs are modest relative to asthma-related costs, e.g., emergency department visits, lost wages from missing work to care for a sick child, and even inhaler and medicine costs (Barnett and Nurmagambetov, 2011).

We exclude the potential energy penalty caused by increased pressure drop across the filters. Generally, high efficiency filters require only small increases in fan power (5 to 13%) depending on the system and climate (Stephens et al. 2010; Zaatari et al. 2014). In California, the energy penalty of moving from MERV 5 to MERV 10-13 filters has been shown to be below 5%, and penalties are most sensitive to cooling cycles (Walker et al. 2013). Cooling cycles have less relevance to study area homes since few have central air conditioning (Du et al. 2011; US Census Bureau, 2013). Thus, only small energy penalties are expected for homes in the study area.

Cost-effectiveness determinations depend on the benefits included. We modeled only reductions in $PM_{2.5}$ from ambient sources and evaluated only confirmed $PM_{2.5}$-associated health impacts on children. Another significant impact of asthma is increased school absenteeism, which causes learning and cost impacts beyond those estimated here. School absences will result from a fraction of asthma symptom-days. Unfortunately, this fraction cannot be estimated from the literature. Filter upgrades in Detroit schools are estimated to reduce asthma symptom days by 17,000 to 30,000 days per year at a total cost of $40 to $63 per classroom per year. With 20 students in a classroom, filter upgrades would cost a total of

$270,000 to $430,000 per year, costs which are matched by the monetized value of 2,800 to 4,400 asthma-related absences a year (2-4 absences per 10 students with asthma per year), based on a value of $98 per school absence (US EPA, 2014b). This analysis suggests that filters would be cost-effective if roughly one in six asthma symptom days led to a school absence.

Filters also reduce PM generated from indoor sources, e.g., resuspended dust, cooking, fireplaces, cigarettes, bacteria, viruses, pet dander, and allergens, several of which are important environmental triggers of asthma (Brown et al. 2014). Increased ventilation rates in schools, which would accompany increased filtration, can reduce illness-related absences among school children in California (Mendell et al. 2013) and improve student academic performance (Haverinen-Shaughnessy et al. 2011; Shaughnessy et al. 2006; Twardella et al. 2012). Adults are susceptible to a number of severe health outcomes associated with $PM_{2.5}$ exposures, e.g., hospitalizations and premature mortality, that also have large monetized values (US EPA, 2009; Chapter 3 Table 3.2), and filtration has been shown to be cost-effective in office buildings, driven largely by reductions in PM-related mortality among adults (Bekö et al. 2008; Montgomery et al. 2015). Similar findings are likely for homes (Fisk et al. 2002). Thus, the true health benefits of filtration may far exceed estimates presented here.

Limitations

Indoor concentrations predicted using steady-state "box" models require a number of assumptions. The analysis simplifies the spatial and temporal variability found in buildings, HVAC operating parameters, time and weather dependence of infiltration and ACRs, and particle composition and size (Breen et al. 2014; Hodas et al. 2012; Isaacs et al. 2013; Stephens, 2015). Not all sources of variability in environmental and building conditions could be accounted for in the Monte Carlo analysis, e.g., seasonal data for schools are not available. Baseline scenarios assume MERV 5 filters; many homes and schools may have more efficient filters, though few appear to use high performance filters. In homes, we assume forced air systems and stand-alone filters are used 20 min per day and continuously, respectively. In reality, few forced air systems allow cycling or reduced fan speed when operated in “fan” mode. As discussed earlier, stand-alone filter use patterns can vary substantially from our assumption for comfort, cost, noise, or other reasons (Batterman et al. 2013).

Health benefits are estimated using HIA approaches developed for ambient air quality. Our exposure metric, C_{eq}, which uses average time-activity data to account for indoor and outdoor exposures (US EPA, 2011), reflects that outdoor concentrations used in exposures in epidemiological studies are proxies for time-weighted exposures to indoor and outdoor concentrations. Other benefits studies have addressed the challenge of estimating health impacts attributable to indoor exposures using CR relationships derived from studies of outdoor concentrations, and three approaches have been used (reviewed in Zhao et al. 2015). First, if CR relationships are linear for the expected range of $PM_{2.5}$ reductions, then concentration reductions from filters are assumed to lead to proportional changes in risk (Bekö et al. 2008). This approach could lead to biased results since the CR relationships for air pollutants are typically non-linear (though they are likely near-linear in the range of exposures considered; Fann et al. 2012). A second approach adjusts the CR coefficient by an I/O ratio such that CR_{indoor}

= CR / R_m to account for smaller changes in indoor concentrations as a result of changes to outdoor concentrations (MacIntosh et al. 2010; Zhao et al. 2015). A third and likely most appropriate approach is to estimate the total intake of $PM_{2.5}$ from exposures indoors and outdoors and use a dose-response (DR) coefficient derived from the CR relationship (Fisk and Chan, 2017). Estimating the intake of $PM_{2.5}$ under different filter scenarios would be similar to the C_{eq} method used in this study but would require additional information in breathing rates in different microenvironments, e.g., homes, schools, and outdoors.

There are other sources of uncertainty that should be considered when interpreting the results of this study. Indoor exposures are based on outdoor concentrations averaged across monitors, with some adjustment for "near-road" schools to account for increased exposures to mobile source emissions of $PM_{2.5}$. There may be considerable spatial variability in $PM_{2.5}$ exposures that is not captured using this method. For example, we are unable to account for the increased exposures associated with buses idling near schools (Kinsey et al. 2007; Ryan et al. 2013). Additionally, the quantitative health impact assessment methods require additional assumptions, e.g., that the CR coefficients drawn from studies elsewhere are applicable to our study population; that there is no threshold below which $PM_{2.5}$ exposures do not cause adverse health impacts; and, that baseline health rates at coarse spatial resolutions (e.g., ZIP codes, county level) are applicable to individual homes and schools. Even with these uncertainties, the quantitative HIA methods presented here offer an estimate of how beneficial filters in schools and homes might be. Our results suggest any increase in filter use is likely to result in health benefits to children living and attending school in and near Detroit.

Conclusions

Here we have combined ambient monitoring data, indoor air quality modeling, and quantitative HIA techniques to estimate the asthma-related benefits for schoolchildren from installing efficient filters in schools and homes. Reductions in indoor concentrations due to filter use depend on building characteristics, filter efficiency, and HVAC or stand-alone filter unit run time. The results suggest using more efficient filters can be an effective strategy for improving asthma-related health outcomes for Detroit-area children, particularly when used in schools. Although the HIA methods used here rely on area-specific data, findings appear generalizable to schools without existing filter programs or with filter programs that meet only the minimum recommendations for filtration. The costs of using enhanced filters in schools are low (less than $5 per student per year). Although the total benefits of filters in homes exceed those in schools, the increased cost of filters in some homes, particularly those without forced-air systems, may be prohibitive. Strategies to reduce the asthma-related burden of ambient air pollution should target schools to reduce exposures for a large number of children and include outreach efforts to encourage parents and other guardians to consider filters to reduced exposures as homes.

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Table 5.1. Parameters used in school and home models.

Parameter	Notation	Unit	Mean	SD[1]	Min[2]	Max[2]	Dist.	Source
Classroom recirculation rate	Q_r	h^{-1}	3.00		2.00	4.00	T	Batterman et al. 2017
Classroom ACR		h^{-1}	1.95		0.10	4.33	T	Batterman et al. 2017
Classroom infiltration rate	Q_{in}	h^{-1}	0.21		0.01	0.54	T	Batterman et al. 2017
Classroom deposition rate	$k_{dep,s}$	h^{-1}	0.10		0.04	0.15	T	Riley et al. 2002
Classroom penetration	P_s	--	0.72		0.39	0.72	T	Riley et al. 2002
Whole house ACR (Sp)		h^{-1}	0.57	0.55	0.1	6.00	L	Du et al. 2011
Whole house ACR (Su)		h^{-1}	0.78	1.03	0.1	6.00	L	Du et al. 2011
Whole house ACR (Fa)		h^{-1}	0.78	0.63	0.1	6.00	L	Du et al. 2011
Whole house ACR (Wi)		h^{-1}	0.88	0.63	0.1	6.00	L	Du et al. 2011
Whole house ACR (Avg)		h^{-1}	0.73	0.76	0.1	6.00	L	Du et al. 2011
Bedroom ACR (Sp)		h^{-1}	1.25	0.87	0.1	6.00	L	Du et al. 2011
Bedroom ACR (Su)		h^{-1}	2.12	2.03	0.1	6.00	L	Du et al. 2011
Bedroom ACR (Fa)		h^{-1}	1.60	1.39	0.1	6.00	L	Du et al. 2011
Bedroom ACR (Wi)		h^{-1}	1.65	1.22	0.1	6.00	L	Du et al. 2011
Bedroom ACR (Avg)		h^{-1}	1.66	1.50	0.1	6.00	L	Du et al. 2011
House deposition rate	$k_{dep,h}$	h^{-1}	0.11		0.05	0.17	T	Riley et al. 2002
House penetration	P_h	--	0.80		0.25	1.00	T	Riley et al. 2002
Ratio of flows, h to b (Sp)	$\alpha_{h,b}$	--	0.54	0.17	0.00	1.00	L	Du et al. 2011
Ratio of flows, h to b (Su)	$\alpha_{h,b}$	--	0.53	0.20	0.00	1.00	L	Du et al. 2011
Ratio of flows, h to b (Fa)	$\alpha_{h,b}$	--	0.58	0.20	0.00	1.00	L	Du et al. 2011
Ratio of flows, h to b (Wi)	$\alpha_{h,b}$	--	0.54	0.18	0.00	1.00	L	Du et al. 2011
Ratio of flows, h to b (Avg)	$\alpha_{h,b}$	--	0.55	0.18	0.00	1.00	L	Du et al. 2011
Ratio of flows, b to h (Sp)	$\alpha_{b,h}$	--	0.25	0.17	0.00	1.00	L	Du et al. 2011
Ratio of flows, b to h (Su)	$\alpha_{b,h}$	--	0.31	0.26	0.00	1.00	L	Du et al. 2011
Ratio of flows, b to h (Fa)	$\alpha_{b,h}$	--	0.24	0.18	0.00	1.00	L	Du et al. 2011
Ratio of flows, b to h (Wi)	$\alpha_{b,h}$	--	0.24	0.15	0.00	1.00	L	Du et al. 2011
Ratio of flows, b to h (Avg)	$\alpha_{b,h}$	--	0.26	0.20	0.00	1.00	L	Du et al. 2011
MERV 5 filter efficiency	ε	--	0.014		0.010	0.192	T	Azimi et al. 2014
MERV 8filter efficiency	ε	--	0.271		0.186	0.384	T	Azimi et al. 2014
MERV 12 filter efficiency	ε	--	0.664		0.611	0.732	T	Azimi et al. 2014
MERV 14 filter efficiency	ε	--	0.714		0.614	0.831	T	Azimi et al. 2014
HEPA filter efficiency	ε	--	0.997		0.995	0.999	T	Azimi et al. 2014

[1] Standard deviation for lognormally-distributed input data

[2] For lognormally-distributed variables, minimum and maximum values represent truncated limits.

Abbreviations: ACR: air change rate; Avg: yearly average; b: bedrooms; Dist: distribution used in the Monte Carlo analysis; Fa: Fall; h: whole house; HEPA: High efficiency particle arrestance; L: lognormal; MERV: Minimum efficiency reporting value; Sp: Spring; Su: Summer; T: triangle; Wi: Winter

Table 5.2. Average volume-normalized inter-zonal flows (h^{-1}) for the three-compartment model. Concentrations are volume-normalized based on the receiving ("to") compartment. For each compartment, the sum of flows in is equal to the sum of flows out.

	"From" compartment			
"To" compartment	Outside (*o*)	Bedroom (*i*)	Living room (*k*)	Other rooms (*j*)
Outside (*o*)	—	1.33	0.20	0.33
Bedroom (*i*)	0.75	—	0.23	0.68
Living room (*k*)	0.45	0.10	—	0.18
Other rooms (*j*)	0.66	0.23	0.30	—

Table 5.3. Parameters used to estimate the marginal costs of filter in homes and schools.

Parameter	Unit	Value	Source/Notes
Electricity	$/kWh	0.1508	Michigan Public Service Commission, 2017
MERV 5 filter	$/filter	2.50	Filter suppliers
MERV 8 filter	$/filter	4.65	Filter suppliers
MERV 12/14 filter	$/filter	10.56	Filter suppliers
HEPA filter (HPA 100)	$ per year	115.00	Honeywell (1 HEPA and 4 pre-filters per year)
HEPA filter (HPA 300)	$ per year	160.00	Honeywell (3 HEPA and 4 pre-filters per year)
Honeywell HPA 100[1]	$/unit	160.00	Honeywell; Annualized cost = $26.80
Honeywell HPA 300[1]	$/unit	300.00	Honeywell; Annualized cost = $50.20
Classroom UV motor consumption	W	180	Trane UV Size 100 (1000 CFM Nominal)
Forced-air blower motor consumption	W	539	Century 1/3 HP Blower Motor
Honeywell HPA 100 consumption	W	52	US EPA, 2017
Honeywell HPA 300 consumption	W	127	US EPA, 2017
School baseline duty cycle	--	0.07	Assumes 20 min/h, 10 h/day, 177 d per year Cetin and Novoselac, 2015
Furnace baseline duty cycle[2]	--	0.1	Thornburg et al. 2004
SA baseline duty cycle	--	0	Assumes no homes have stand-alone filters

[1] Annualized cost assumes an 8 year lifecycle and 7% discount rate

[2] Studies estimate a median duty cycle of roughly 20% for homes in Austin, Texas using central heating and air conditioning (Cetin and Novoselac, 2015), 21% for homes in Tampa, Florida, and 6% for homes in North Carolina (Thornburg et al. 2004). For homes in Detroit, we assume a baseline duty cycle of 0.1, half that of Texas and Florida homes, since few homes in Detroit have central air conditioning and therefore do not run their systems during the summer.

Table 5.4. Average (standard deviation) I/O ratios by season and filter rating for classrooms, homes with forced-air systems, and bedrooms, living rooms, and other rooms in the three-compartment model.[1]

	Classrooms				Homes with forced-air system				Bedrooms		Living Rooms		Other rooms	
	Filter rating													
	5	8	12	14	5	8	12	14	NA	HEPA	NA	HEPA	NA	HEPA
Sp	0.86 (0.09)	0.47 (0.1)	0.17 (0.04)	0.15 (0.04)	0.54 (0.16)	0.33 (0.15)	0.22 (0.12)	0.21 (0.12)	0.55 (0.16)	0.08 (0.05)	0.51 (0.16)	0.05 (0.04)	0.55 (0.15)	0.38 (0.12)
Su	0.86 (0.09)	0.47 (0.11)	0.17 (0.04)	0.15 (0.04)	0.55 (0.17)	0.36 (0.17)	0.25 (0.14)	0.24 (0.14)	0.58 (0.17)	0.1 (0.07)	0.53 (0.17)	0.06 (0.05)	0.57 (0.16)	0.38 (0.14)
Fa	0.86 (0.09)	0.46 (0.1)	0.17 (0.04)	0.15 (0.04)	0.58 (0.16)	0.39 (0.15)	0.27 (0.13)	0.26 (0.13)	0.57 (0.16)	0.09 (0.06)	0.55 (0.16)	0.06 (0.05)	0.57 (0.16)	0.39 (0.13)
Wi	0.86 (0.10)	0.46 (0.11)	0.17 (0.05)	0.15 (0.04)	0.60 (0.16)	0.42 (0.15)	0.30 (0.13)	0.29 (0.13)	0.59 (0.16)	0.10 (0.06)	0.58 (0.16)	0.07 (0.05)	0.60 (0.16)	0.41 (0.13)
Avg	0.86 (0.09)	0.46 (0.11)	0.17 (0.04)	0.15 (0.04)	0.57 (0.16)	0.38 (0.16)	0.26 (0.13)	0.25 (0.13)	0.57 (0.16)	0.09 (0.06)	0.54 (0.16)	0.06 (0.05)	0.57 (0.16)	0.39 (0.13)

[1] Assumes UV runs continuously while children are in classrooms (7 h day^{-1}); forced air systems run 20 min h^{-1}; and stand-alone-filters run continuously when children are home (14.4 h day^{-1}).

Abbreviations: Avg: average; HEPA: High efficiency particle arrestance; Fa: fall; NA: no filter used; Sp: spring; Su: summer; Wi: winter

Table 5.5. Current (baseline) asthma-related impacts for school-aged children in the study area. Includes total impacts and impacts attributable to $PM_{2.5}$ exposures during the school year (September 1 to June 15) and calendar year. Results rounded to 2 significant figures; 95% CI in parentheses.[1]

	Estimated Incidence (per year)	Impacts attributable to $PM_{2.5}$ exposures[2,3] (per school year)	Impacts attributable to $PM_{2.5}$ exposures[3] (per calendar year)
Hospitalization (6-18)	480	8 (2–12)	17 (4–24)
Emergency department visits (6-18)	5300	150 (39–250)	300 (79–510)
Exacerbation (cough, 6-14)	1,400,000	83,000 (0–160,000)	170,000 (0–330,000)
Exacerbation (wheeze, 6-14)	860,000	6,600 (1,100–120,00)	14,000 (2,400–24,000)
Exacerbation (shortness of breath, 6-14)	820,000	8,400 (0–17,000)	17,000 (0–35,000)
DALYS (years)	3,400	110 (1–210)	220 (3–430)
Monetized Impacts (2010 $million)	190	5.8 (0.1–11.1)	12.2 (0.2–23.1)
Attributable fraction (%)[4]		3.1	6.5

1 95% confidence limits are left-truncated at 0

2 Considers only 177 days during the school year

3 Assumes UVs with MERV 5 filters run continuously while children are in classrooms, homes with forced air systems have MERV 5 filters and run 20 min/hour, and homes without forced air systems do not use stand-alone-filters

[4] Percent of total DALYs due to DALYs attributable to indoor $PM_{2.5}$ exposures

Table 5.6. Asthma-related health benefits per year among children from replacing MERV 5 filters with more efficient filters in schools or homes. Health benefits are estimated based on the change in “equivalent exposure concentration” metric (C_{eq}) and presented as the number of avoided health outcomes per year. 95% CI for health impact estimates in parentheses.

	Avoided impacts due to filters in all schools			Avoided impacts due to filters at near-road schools			Avoided impacts due to filters in homes[1]		
	MERV Rating								
Outcome (cases)	8	12	14	8	12	14	8	12	14
Asthma hospitalization	1 (0–2)	2 (1–3)	3 (1–4)	0 (0–1)	1 (0–1)	1 (0–1)	2 (0–3)	3 (1–4)	3 (1–4)
Asthma ED visit	25 (7–41)	43 (11–70)	45 (12–75)	7 (2–11)	12 (3–19)	12 (3–20)	33 (9–55)	48 (13–78)	49 (13–81)
Cough	14,000 (0–25,000)	23,000 (0–43,000)	25,000 (0–45,000)	2,900 (0–5,000)	5,000 (0–8,900)	5,200 (0–9,300)	19,000 (0–34,000)	27,000 (0–48,000)	27,000 (0–49,000)
Wheeze	1,200 (200–2,000)	1,900 (330–3,400)	2,100 (350–3,600)	240 (42–430)	420 (73–740)	440 (75–770)	1,600 (270–2,800)	2,200 (380–3,900)	2,300 (390–4,000)
Shortness of breath	1,500 (0–2,900)	2,400 (0–4,900)	2,600 (0–5,200)	310 (0–600)	530 (0–1,100)	550 (0–1,100)	2,000 (0–3,900)	2,800 (0–5,600)	2,900 (0–5,800)
DALYs (years)	18 (0–33)	31 (0–56)	33 (0–59)	4 (0–7)	7 (0–12)	7 (0–12)	24 (0–44)	35 (0–64)	36 (0–65)
Monetized benefit ($)[2]	1.0 (0–1.8)	1.7 (0–3)	1.8 (0–3.2)	0.2 (0–0.4)	0.4 (0–0.6)	0.4 (0–0.7)	1.3 (0–2.4)	1.9 (0–3.4)	2.0 (0–3.5)
Reduction in DALYs (%)[3]	8	13	14	10	16	17	11	16	16

1 For homes, we assume that houses without forced-air systems use stand-alone HEPA filters in children’s bedrooms and living rooms.
2 Reported in millions
3 Calculated as the reduction in DALYs compared to baseline impacts. For schools, the percent reduction is scaled by 0.48 to reflect that students are only in school 177 days per year.
Abbreviations: DALY: disability-adjusted life year; ED: emergency department; MERV: minimum efficiency reporting value

Table 5.7. Marginal costs ($ per year per building) of more efficient filters in schools and homes in the study area. Costs include electricity (from longer duty cycles) and filter replacement cost. For stand-alone filters, marginal costs include the purchase of the stand-alone units in the "first year" total cost. Estimated costs for scenarios in Table 5.6 are emphasized.

	Marginal cost ($/building-year)								
	Unit ventilators			Forced-air systems			Stand-alone filters		
Duty Cycle	MERV 5	MERV 8	MERV 12/14	MERV 5	MERV 8	MERV 12/14	HPA 100	HPA 300	Total
0.1	7	16	39	0	9	32	149	227	376
0.2	***31***	***40***	***63***	71	80	103	156	244	399
0.3	55	63	87	***142***	***151***	***175***	162	261	423
0.4	78	87	111	214	222	246	169	277	447
0.5	102	111	134	285	293	317	176	294	470
0.6	126	135	158	356	364	388	***183***	***311***	***494***
0.7	150	158	182	427	436	459	190	328	518
0.8	174	182	206	498	507	530	197	344	541
0.9	197	206	230	569	578	602	204	361	565
1	221	230	253	641	649	673	210	378	588

Figure 5.1. Depiction of mass balance models for (A) single compartment model for houses with forced-air systems, and (B) three-compartment model for houses without forced-air systems using stand-alone filter units in child's bedroom and living room. $PM_{2.5}$ mass flows are depicted by arrows and equations.

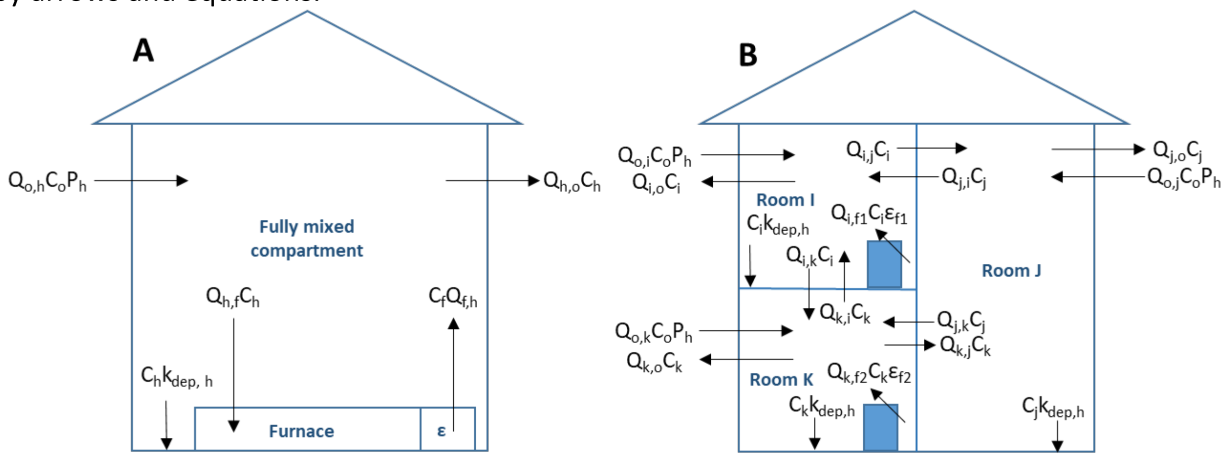

Figure 5.2. Boxplots showing I/O ratios for (A) classrooms with unit ventilators, (B) homes with forced-air systems, and (C) homes with stand-alone filter units in bedrooms and living rooms. Dots represent mean values. 5th, 25th, 50th (bar), 75th, and 95th percentiles shown.

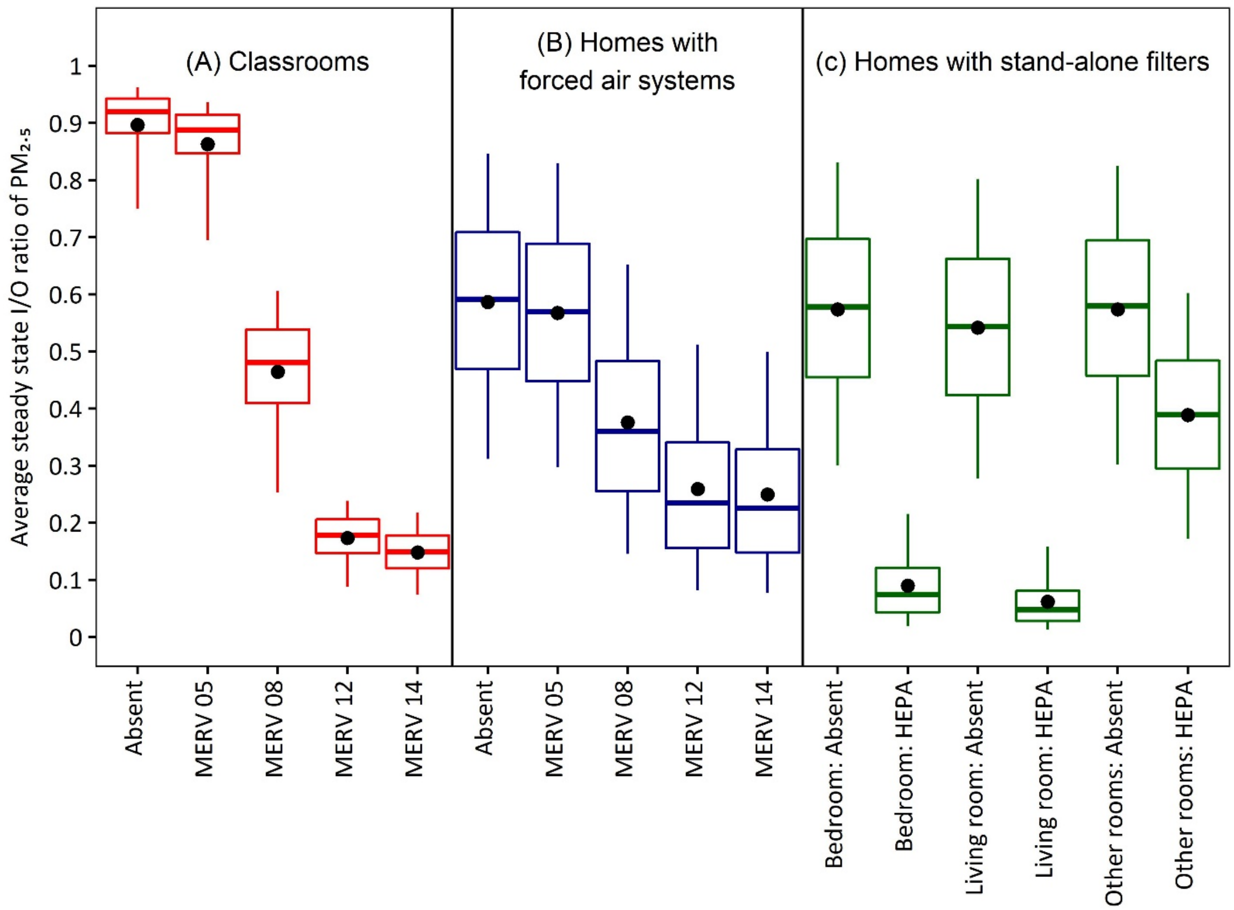

Figure 5.3. Sensitivity analysis of duty cycle on I/O ratios for $PM_{2.5}$ in (A) classrooms, (B) homes with forced-air systems, and (C) bedrooms, living rooms, and other rooms in houses when using stand-alone HEPA filters. Error bars show standard deviation of the mean estimates.

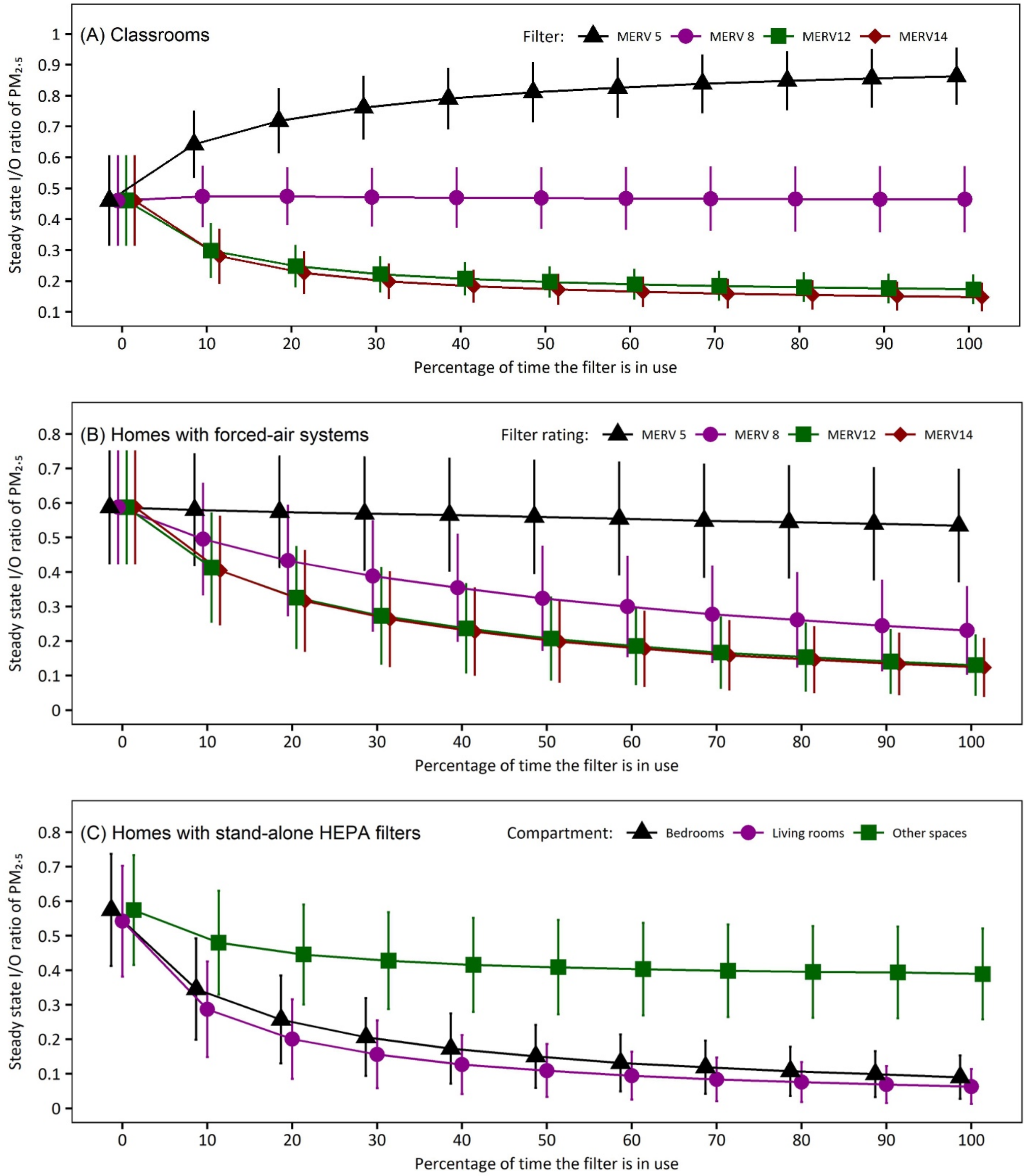

Figure 5.4. Tornado plots showing the change in mean indoor concentrations of $PM_{2.5}$ by IAQ model inputs for (A) classrooms using MERV 8 filters, (B) homes using MERV 8 filters, and (C) homes using stand-alone units with HEPA filters.

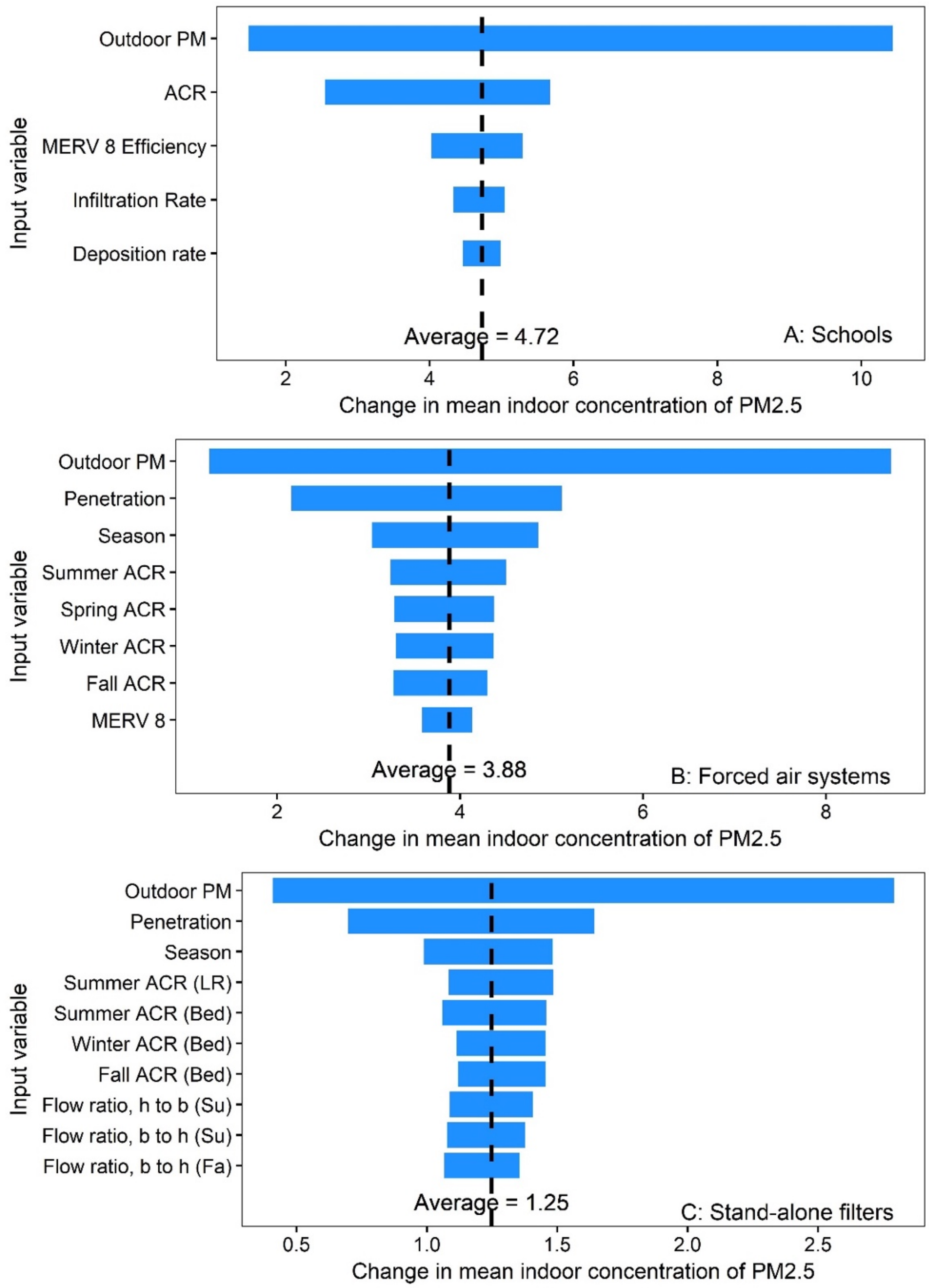

Figure abbreviations: ACR: air change rate; B: bedroom; Fa: Fall; HEPA: High Efficiency Particle Arrestance; H: whole house; LR: living room; MERV: minimum efficiency reporting value; Su: Summer

Appendix A5

SUPPLEMENTAL MATERIALS FOR CHAPTER 5

Supplemental Results

The following describes the results of the supplemental benefits analysis assuming MERV 8 filters are used in all classrooms in the study area.

Benefits of filters in school when using a MERV 8 in classrooms at baseline

The primary analysis assumes classroom UVs use an inefficient MERV 5 filter at baseline. However, US EPA's Tools for Schools program recommends classrooms use a MERV 8 filter at minimum (US EPA 2012b), and many classrooms in the area may follow this recommendation. Table A5.7 summarizes the school-year and annual health impacts attributable to indoor $PM_{2.5}$ exposures to outdoor pollutants, assuming classroom UVs use MERV 8 filters at baseline (all other assumptions are the same as for the analysis presented in Table 5.6). Attributable impacts for the school year (89 DALYs and $4.9 million per year) and the full year (210 DALYs and $11.2 million per year) are 8% lower than the impacts estimated when assuming classrooms use MERV 5 filters at baseline (Table A5.7; Table 5.6). This modest decrease in attributable impacts reflects that MERV 8 filters are moderately efficient ($\varepsilon = 0.27$, Table 5.1) compared to MERV 5 filters (ε = 0.014, Table 5.1) and that children only spend a portion of their time in school (less than 8 hours per day, 177 days per year). The benefits of using filters in schools and homes are lower when assuming classrooms have MERV 8 filters at baseline. For schools, increasing from a MERV 8 to a MERV 12 or MERV 14 filters reduces annual health impacts by 6 and 7%, respectively (Table A5.8). This is lower than the estimated 13 and 14% reductions when assuming MERV 5 filters at baseline (Table 5.6). The marginal cost of updating from a MERV 8 to a MERV 12 filter in schools ($55 per classroom per year or $27 per student with asthma per year; Table A5.9) is 13% lower than the marginal cost of increasing from a MERV 5 to MERV 12 filter; electricity costs remain the same, but the difference in cost is lower. The monetized benefits of increasing from a MERV 8 to a MERV 12 filter in schools ($64 per student with asthma per year; Table A5.8) are more than twice the marginal costs ($27 per student with asthma per year).

For homes, upgrading inefficient filters (MERV5) to MERV 8, 12, or 14 filters (assuming schools have MERV 8 filters) reduces annual health impacts by 4, 9, and 9%, respectively (Table A5.8). The marginal costs of filters in homes remains unchanged ($142 to $175 per year for homes with forced air systems and $494 for homes using stand-alone filters; Table 5.7) but the benefits per child with asthma are lower ($109 to $164 per child with asthma per year. Benefits of filters in homes are impacted by the filter type used in schools because the C_{eq} accounts for total exposures throughout the day and baseline exposures in schools, which account for 32% of the time-weighted average exposure on school days, are 47% lower under the MERV 8 scenario compared to the MERV 5 case (Table 5.4).

Supplemental Tables

Table A5.1. Summary of seasonal inter-zonal flows (h^{-1}) for the three-compartment model. Concentrations are volume-normalized based on the receiving ("to") compartment. For each compartment, the sum of flows in is equal to the sum of flows out.

	"From" compartment			
"To" compartment:	Outside (*o*)	Bedroom (*i*)	Living room (*k*)	Other rooms (*j*)
Spring				
Outside (*o*)	—	1.00	0.17	0.26
Bedroom (*i*)	0.58	—	0.17	0.51
Living room (*k*)	0.35	0.08	—	0.14
Other rooms (*j*)	0.51	0.17	0.23	—
Summer				
Outside (*o*)	—	1.68	0.14	0.41
Bedroom (*i*)	1.00	—	0.28	0.84
Living room (*k*)	0.48	0.10	—	0.20
Other rooms (*j*)	0.75	0.34	0.36	—
Fall				
Outside (*o*)	—	1.27	0.25	0.30
Bedroom (*i*)	0.67	—	0.23	0.70
Living room (*k*)	0.47	0.11	—	0.20
Other rooms (*j*)	0.68	0.21	0.30	—
Winter				
Outside (*o*)	—	1.30	0.32	0.38
Bedroom (*i*)	0.76	—	0.22	0.67
Living room (*k*)	0.54	0.12	—	0.22
Other rooms (*j*)	0.72	0.23	0.32	—

Table A5.2. Distribution of daily mean $PM_{2.5}$ concentrations across all monitors and the daily mean "background" and "local increment" concentrations (μg/m^3) based on measurements recorded at 12 area monitors, 2011-2015.

$PM_{2.5}$ Metric	Period	Mean	SD	25th	50th	75th	95th	99th	Max
Daily average (μg/m^3)	School days	9.4	5.5	0.8	4.1	5.5	7.3	8.7	9.1
	All year	9.8	5.5	0.8	5.6	8.8	12.6	20.2	26.0
Background (μg/m^3)	School days	8.2	5.2	0.6	3.4	4.5	5.9	7.3	7.5
	All year	8.5	5.1	0.6	4.7	7.4	11.0	18.5	23.3
Local increment (μg/m^3)	School days	4.1	2.7	0.5	1.8	2.5	3.3	3.7	3.8
	All year	4.1	3.1	0.4	2.3	3.4	4.8	9.1	15.3

Table A5.3. Current (baseline) asthma-related impacts for school-aged children in the study area. Includes total impacts and impacts attributable to $PM_{2.5}$ exposures during the school year (September 1 to June 15) and calendar year assuming children spend *no time outdoors*. Impact estimates have been rounded to 2 significant figures. 95% CI for attributable impact estimates in parentheses.[1]

	Estimated Incidence (per year)	Impacts attributable to $PM_{2.5}$ exposures[3] (per school year[2])	Impacts attributable to $PM_{2.5}$ exposures[3] (per calendar year)
Hospitalization (6-18)	480	8 (2 – 12)	17 (4–24)
Emergency department visits (6-18)	5300	150 (39 – 250)	300 (79–510)
Exacerbation (cough, 6-14)	1,400,000	83,000 (0 – 160,000)	170,000 (0–330,000)
Exacerbation (wheeze, 6-14)	860,000	6,600 (1140 – 12,000)	14,000 (2,400–25,000)
Exacerbation (shortness of breath, 6-14)	820,000	8,400 (0 – 17,000)	18,000 (0–35,000)
DALYS (years)	3,400	108 (1 – 210)	220 (3–430)
Monetized Impacts (2010 $million)	190	5.9 (0.1 – 11.1)	12.2 (0.2–23.1)
Attributable fraction (%)[4]		3.2	6.5

[1] 95% confidence limits are left-truncated at 0

[2] Considers only 177 days during the school year

[3] Assumes UVs with MERV 5 filters run continuously while children are in classrooms, homes with forced air systems have MERV 5 filters and run 20 min/hour, and homes without forced air systems do not use stand-alone-filters

[4] Percent of total DALYs due to DALYs attributable to indoor $PM_{2.5}$ exposures

Table A5.4. Current (baseline) asthma-related impacts for school-aged children in the study area. Includes total impacts and impacts attributable to $PM_{2.5}$ exposures during the school year (September 1 to June 15) and calendar year assuming children spend *6 h day^{-1} outdoors*. Impact estimates have been rounded to 2 significant figures. 95% CI for attributable impact estimates in parentheses.[1]

	Estimated Incidence (per year)	Impacts attributable to $PM_{2.5}$ exposures[2,3] (per school year)	Impacts attributable to $PM_{2.5}$ exposures[3] (per calendar year)
Hospitalization (6-18)	480	8 (2 – 12)	17 (4–24)
Emergency department visits (6-18)	5300	150 (39 – 250)	300 (79–510)
Exacerbation (cough, 6-14)	1,400,000	83,000 (0 – 160,000)	170,000 (0–330,000)
Exacerbation (wheeze, 6-14)	860,000	6,600 (1,100 – 12,000)	14,000 (2,400–24,000)
Exacerbation (shortness of breath, 6-14)	820,000	8,400 (0 – 17,000)	17,000 (0–35,000)
DALYS (years)	3,400	108 (1 – 210)	220 (3–430)
Monetized Impacts (2010 $million)	190	5.9 (0.1 – 11.1)	12.2 (0.2–23.1)
Attributable fraction (%)[4]		3.2	6.5

[1] 95% confidence limits are left-truncated at 0

[2] Considers only 177 days during the school year

[3] Assumes UVs with MERV 5 filters run continuously while children are in classrooms, homes with forced air systems have MERV 5 filters and run 20 min/hour, and homes without forced air systems do not use stand-alone-filters

[4] Percent of total DALYs due to DALYs attributable to indoor $PM_{2.5}$ exposures

Table A5.5. Asthma-related health benefits per year among children from replacing MERV 5 filters with more efficient filters in schools or homes assuming children *spend no time outdoors each day*. See Table 5.6 for additional details.

	Avoided impacts due to filters in all schools			Avoided impacts due to filters at near-road schools			Avoided impacts due to filters in homes[1]		
	MERV Rating								
Outcome (cases)	8	12	14	8	12	14	8	12	14
Asthma hospitalization	1 (0–2)	3 (1–4)	3 (1–4)	0 (0–1)	1 (0–1)	1 (0–1)	2 (1–3)	3 (1–4)	3 (1–4)
Asthma ED visit	27 (7–44)	47 (12–77)	48 (13–80)	8 (2–12)	13 (4–22)	14 (4–23)	35 (9–58)	50 (13–82)	51 (14–84)
Cough	15,000 (0–26,000)	26,000 (0–46,000)	26,000 (0–48,000)	3,200 (0–5,600)	5,600 (0–10,000)	5,800 (0–10,000)	20,000 (0–35,000)	28,000 (0–51,000)	29,000 (0–52,000)
Wheeze	1,200 (210–2,200)	2,100 (370–3,700)	2,200 (380–3,900)	270 (47–480)	460 (80–820)	480 (84–860)	1,600 (280–2,900)	2,300 (400–4,100)	2,400 (410–4,200)
Shortness of breath	1,500 (0–3,100)	2,700 (0–5,400)	2,800 (0–5,500)	340 (0–700)	590 (0–1,200)	610 (0–1,200)	2,100 (0–4,100)	3,000 (0–5,900)	3,000 (0–6,000)
DALYs (years)	19 (0–35)	33 (0–61)	35 (0–63)	4 (0–7)	7 (0–13)	8 (0–14)	26 (0–47)	37 (0–67)	38 (0–68)
Monetized benefit ($)[2]	1 (0–1.9)	1.8 (0–3.3)	1.9 (0–3.4)	0.2 (0–0.4)	0.4 (0–0.7)	0.4 (0–0.8)	1.4 (0–2.5)	2 (0–3.6)	2 (0–3.7)
Reduction in DALYs (%)[3]	9	15	15	11	18	19	12	16	17

[1] For homes, we assume that houses without forced-air systems use stand-alone HEPA filters in children's bedrooms and living rooms.
[2] Reported in millions
[3] Calculated as the reduction in DALYs compared to baseline impacts. For schools, the percent reduction is scaled by 0.48 to reflect that students are only in school 177 days per year.
Abbreviations: DALY: disability-adjusted life year; ED: emergency department; MERV: minimum efficiency reporting value

Table A5.6. Asthma-related health benefits per year among children from replacing MERV 5 filters with more efficient filters in schools or homes assuming children *spend 6 h day^{-1} outdoors*. See Table 5.6 for additional details.

	Avoided impacts due to filters in all schools			Avoided impacts due to filters at near-road schools			Avoided impacts due to filters in homes[1]		
	MERV Rating								
Outcome (cases)	8	12	14	8	12	14	8	12	14
Asthma hospitalization	1 (0–2)	2 (1–3)	2 (1–3)	0 (0–0)	1 (0–1)	1 (0–1)	2 (0–2)	2 (1–4)	2 (1–4)
Asthma ED visit	22 (6–36)	38 (10–63)	40 (11–66)	6 (2–9)	10 (3–16)	10 (3–16)	30 (8–50)	44 (12–72)	45 (12–74)
Cough	12,000 (0–22,000)	21,000 (0–38,000)	22,000 (0–40,000)	2,400 (0–4,100)	4,100 (0–7,200)	4300 (0–7500)	17,000 (0–30,000)	24,000 (0–44,000)	25,000 (0–45,000)
Wheeze	1,000 (170–1,700)	1,800 (300–3,100)	1,800 (320–3,300)	200 (35–350)	340 (59–600)	360 (62–630)	1,400 (240–2,500)	2,000 (350–3,600)	2,100 (360–3,700)
Shortness of breath	1,200 (0–2,500)	2,200 (0–4,500)	2300 (0–4,700)	250 (0–500)	430 (0–900)	450 (0–900)	1,800 (0–3,500)	2,600 (0–5,100)	2,600 (0–5,300)
DALYs (years)	16 (0–28)	28 (0–51)	29 (0–53)	3 (0–5)	5 (0–10)	6 (0–10)	22 (0–40)	32 (0–58)	33 (0–60)
Monetized benefit ($)[2]	0.9 (0–1.5)	1.5 (0–2.7)	1.6 (0–2.9)	0.2 (0–0.3)	0.3 (0–0.5)	0.3 (0–0.5)	1.2 (0–2.2)	1.7 (0–3.1)	1.8 (0–3.2)
Reduction in DALYs (%)[3]	7	12	13	8	13	14	10	14	15

[1] For homes, we assume that houses without forced-air systems use stand-alone HEPA filters in children's bedrooms and living rooms.
[2] Reported in millions
[3] Calculated as the reduction in DALYs compared to baseline impacts. For schools, the percent reduction is scaled by 0.48 to reflect that students are only in school 177 days per year.
Abbreviations: DALY: disability-adjusted life year; ED: emergency department; MERV: minimum efficiency reporting value

Table A5.7. Current (baseline) asthma-related impacts for school-aged children in the study area, including total impacts and impacts attributable to $PM_{2.5}$ exposures during the school year (September 1 to June 15) and calendar year assuming a MERV 8 filter in all schools at baseline.

	Estimated Incidence (per year)	Impacts attributable to $PM_{2.5}$ exposures[3] (per school year[2])	Impacts attributable to $PM_{2.5}$ exposures[3] (per calendar year)
Hospitalization (6-18)	480	7 (2 – 10)	15 (4 – 23)
Emergency department visits (6-18)	5300	120 (32 – 210)	280 (73 – 471)
Exacerbation (cough, 6-14)	1,400,000	69,000 (0 – 130,000)	160,000 (0 – 300,000)
Exacerbation (wheeze, 6-14)	860,000	5,500 (940 – 9,700)	13,000 (2,200 – 23,000)
Exacerbation (shortness of breath, 6-14)	820,000	6,900 (0 – 14,000)	16,000 (0 – 32,000)
DALYS (years)	3,400	89 (1 – 170)	210 (3 – 400)
Monetized Impacts (2010 $million)	190	4.9 (0.1 – 9.3)	11.2 (0.2 – 21.4)
Attributable fraction (%)[4]		7 (2 – 10)	15 (4 – 23)

[1] 95% confidence limits are left-truncated at 0

[2] Considers only 177 days during the school year

[3] Assumes UVs with MERV 8 filters run continuously while children are in classrooms, homes with forced air systems have MERV 5 filters and run 20 min/hour, and homes without forced air systems do not use stand-alone-filters

[4] Percent of total DALYs due to DALYs attributable to indoor $PM_{2.5}$ exposures

Table A5.8. Asthma-related health benefits per year among children from replacing MERV 8 filters in schools and MERV 5 filters in homes with more efficient filters. See Table 5.6 for additional details.

	Avoided impacts due to filters in all schools			Avoided impacts due to filters at near-road schools			Avoided impacts due to filters in homes[1]		
	MERV Rating								
Outcome (cases)	8	12	14	8	12	14	8	12	14
Asthma hospitalization	—	1 (0–1)	1 (0–2)	—	0 (0–0)	0 (0–0)	1 (0–1)	1 (0–2)	1 (0–2)
Asthma ED visit	—	17 (5–29)	20 (5–33)	—	5 (1–8)	5 (1–9)	10 (3–16)	24 (6–40)	26 (7–42)
Cough	—	10,000 (0–18,000)	11,000 (0–20,000)	—	2,100 (0–3,900)	2,300 (0–4,200)	6,000 (0–10,000)	14,000 (0–25,000)	14,000 (0–26,000)
Wheeze	—	800 (130–1,400)	900 (160–1,600)	—	180 (30–310)	190 (33–340)	500 (80–800)	1,100 (190–2,000)	1,200 (210–2,100)
Shortness of breath	—	1,000 (0–2,000)	1,100 (0–2,300)	—	220 (0–400)	240 (0–500)	600 (0–1,200)	1,400 (0–2,800)	1,500 (0–3,000)
DALYs (years)	—	13 (0–23)	14 (0–27)	—	3 (0–5)	3 (0–6)	7 (0–13)	18 (0–32)	19 (0–34)
Monetized benefit ($)[2]	—	0.7 (0–1.3)	0.8 (0–1.4)	—	0.2 (0–0.3)	0.2 (0–0.3)	0.4 (0–0.7)	1 (0–1.8)	1 (0–1.8)
Reduction in DALYs (%)[3]	—	6	7	—	9	10	4	9	9

[1] For homes, we assume that houses without forced-air systems use stand-alone HEPA filters in children's bedrooms and living rooms.
[2] Reported in millions
[3] Calculated as the reduction in DALYs compared to baseline impacts. For schools, the percent reduction is scaled by 0.48 to reflect that students are only in school 177 days per year.
Abbreviations: DALY: disability-adjusted life year; ED: emergency department; MERV: minimum efficiency reporting value

Table A5.9. Marginal costs ($ per building per year) of increased filter use and more efficient filters in schools assuming MERV 8 filters are used at baseline. Costs include electricity (from longer duty cycles) and filter replacement cost.

	Marginal cost ($/building-year)	
Duty Cycle	MERV 8	MERV 12/14
0.1	7	31
0.2	**31**	**55**
0.3	55	78
0.4	78	102
0.5	102	126
0.6	126	150
0.7	150	173
0.8	174	197
0.9	197	221
1	221	245

Supplemental Figures

Figure A5. 1. Sensitivity analysis of duty cycle on I/O ratios for $PM_{2.5}$ in “tight” homes with lower air change rates and particle penetration factors. Error bars show standard deviation of the mean estimates from the MC analysis.

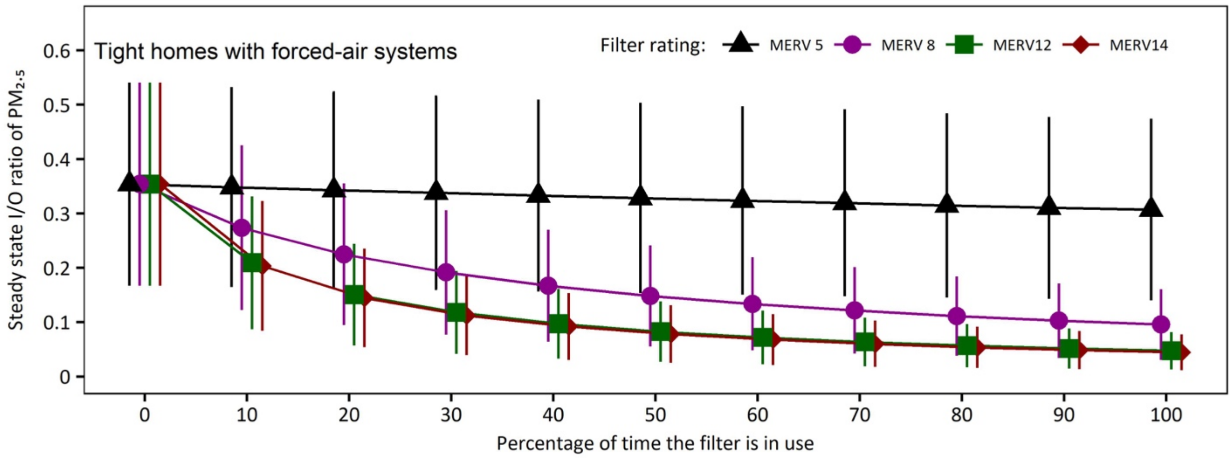

Figure A5. 2. Tornado plots for MERV 5, MERV 12, and MERV 14 filters in schools and homes with forced air systems.

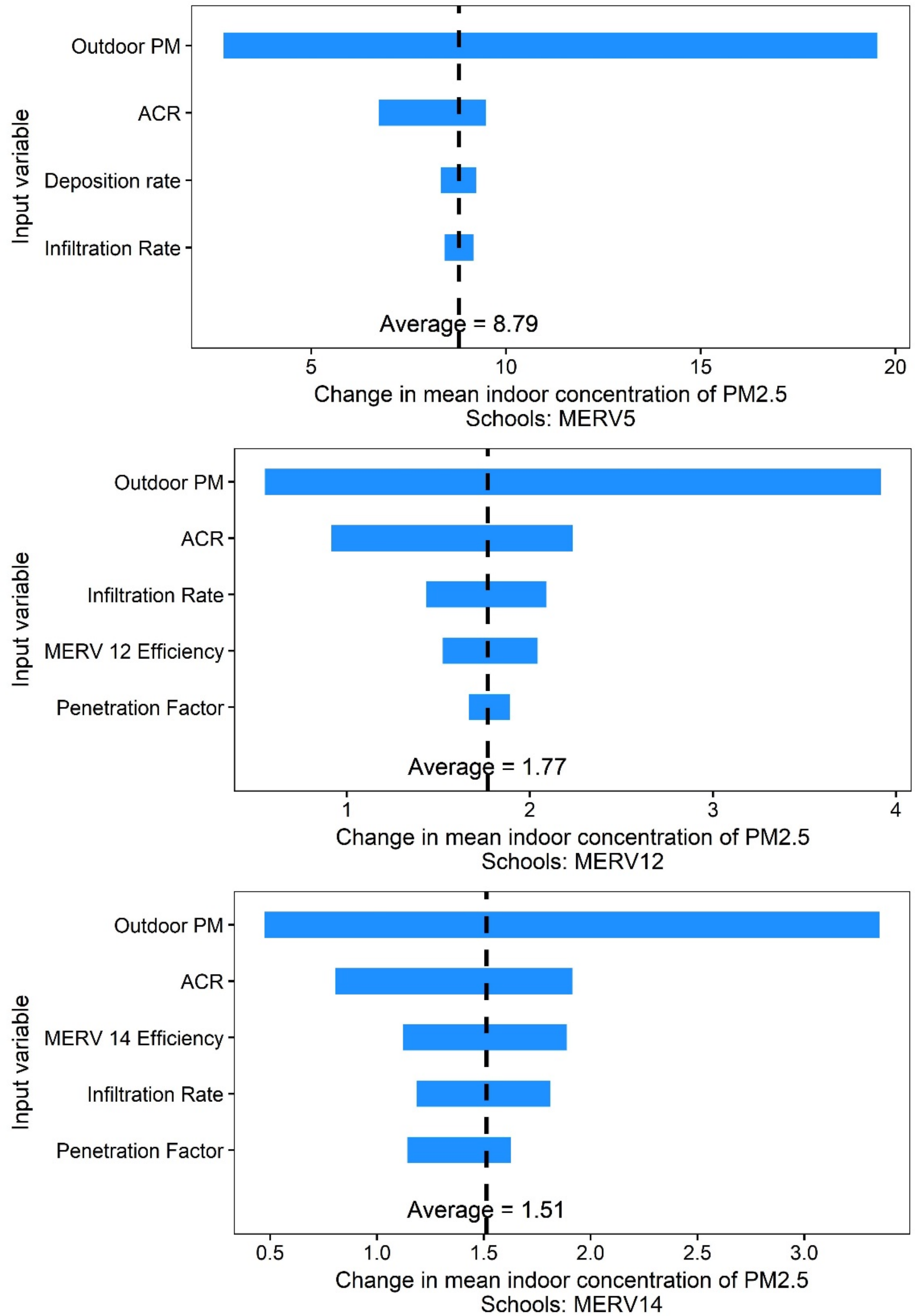

Figure A5. 2 (continued). Tornado plots for MERV 5, MERV 12, and MERV 14 filters in schools and homes with forced air systems.

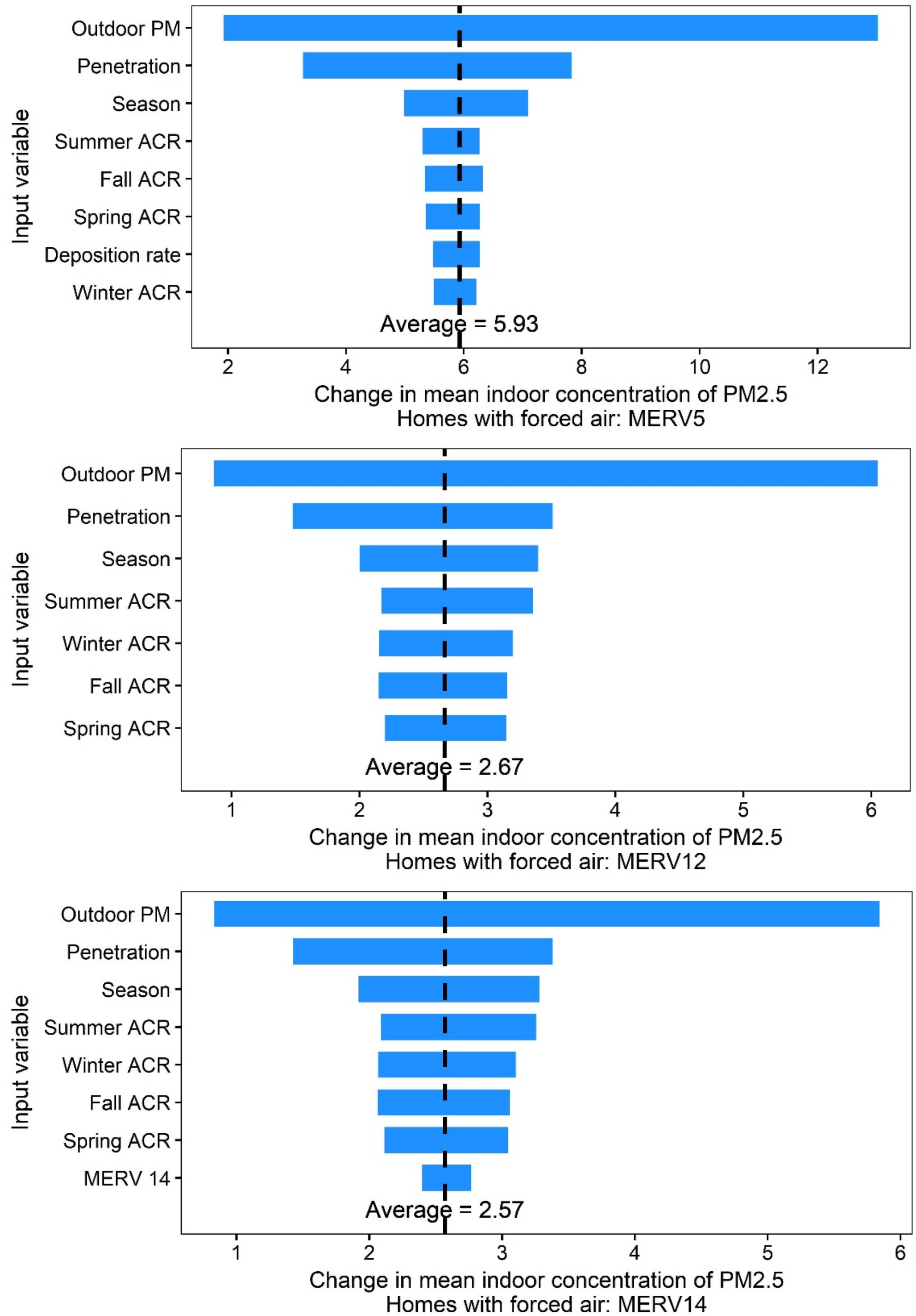

Figure abbreviations: ACR: air change rate; MERV: minimum efficiency reporting value

Chapter 6

CONCLUSION

This dissertation has explored the use of quantitative health impact assessment (HIA) methods at the urban and intra-urban scales to quantify the burden of disease due to ambient air pollutants and to estimate the potential health benefits of strategies that reduce emissions of or exposure to these air pollutants. The analyses presented here considered the magnitude of health impacts as well as their distribution across the study area (which includes Detroit, MI and several adjacent cities) and across demographic and socioeconomic subgroups. The specific aims of this dissertation were: to identify quantitative health impact metrics that are appropriate for studies meant to inform air quality management decisions (Specific Aim 1); to assess the public health burden and health disparities attributable to current levels of ambient air pollutants in the study area using a quantitative impact assessment framework (Specific Aim 2); and to evaluate selected strategies for reducing air pollutant concentrations, exposures and health impacts in the study area using quantitative HIA methods (Specific Aim 3). These aims were addressed in Chapters 2 through 5.

This chapter, the conclusion of this work, has five sections. The next section summarizes the main findings from each specific aim in this dissertation. The remaining sections discuss the tradeoffs of selected air quality management (AQM) strategies for the study area; how quantitative HIA methods can be used to guide local decision making; how including HIA methods in the environmental decision-making process can potentially lead state and national environmental policy towards more equitable goals; barriers and challenges for local scale assessments, including communicating results to decision makers; and, directions for future studies. The chapter ends with overall conclusions about the work.

Summary of main findings

The analysis in Chapter 2, which addressed Specific Aim 1, compared health impact metrics relevant for evaluating air quality management (AQM) strategies. These metrics included, for example, the number of attributable cases, disability-adjusted life years (DALYs), monetized impacts, and functional-unit based impacts (i.e., impacts per ton of pollutant emitted). These metrics were evaluated against a set of criteria that included their comprehensiveness and relevance to local scale assessments. The analysis indicated the need for metrics that are comprehensive with respect to outcomes and the number of people affected, and that clearly communicate direct and indirect impacts and uncertainty. Further, metrics should use local data (e.g., baseline rates from the study population), incorporate outcomes of high public health importance, and represent the spatial and temporal dimensions of impacts. Because no single metric met all the specified criteria, a suite of metrics was recommended, specifically attributable cases, disability-adjusted life years (DALYs), and monetized impacts. The number of attributable cases or mortality and morbidity provides decision makers with a sense of how many people are impacted by a given AQM decision, and aggregating attributable cases as

DALYs provides a useful summary metric that considers the duration and severity of air-pollution related health impacts. Monetizing health impacts or benefits is also recommended because many decision makers are familiar with monetized impacts and this metric can be used in other policy evaluations, e.g., cost-effectiveness or cost-benefit analyses.

Chapter 3 addressed Specific Aim 2 and presented a burden of disease assessment for the study area. The analysis reported health-related impacts for four criteria pollutants—$PM_{2.5}$, O_3, SO_2 and NO_2—and diesel particulate matter using the metrics identified in Chapter 2 as particularly relevant for AQM studies at the local scale, that is, attributable cases, DALYs, and monetized impacts. The analysis was extended to include inequality metrics relevant for cumulative impact and environmental justice assessments. The results suggested that exposure to ambient pollutants continues to have a substantial health burden on study area residents, and that the health burden is driven by $PM_{2.5}$ and O_3 exposures that arise primarily from regional sources. While local point and mobile sources of $PM_{2.5}$, NO_2, and SO_2 imposed lower health impacts compared to regional sources of $PM_{2.5}$ and O_3, these sources contributed most to the inequality of the health burden experienced by socially disadvantaged populations within the study area boundaries. The inequality assessment found that point source emissions disproportionately impacted Hispanic/Latino residents, and that mobile source emissions disproportionately impact low-income residents. Further, the inequality results in this chapter suggest that the typical approach for including air quality in cumulative impact studies, i.e., using exposure concentrations as a proxy for health burden, underestimated the inequality at the local scale and potentially missed important burdens that should be included in a cumulative impact or environmental justice studies.

Chapter 4, the first of two chapters to address Specific Aim 3, investigated alternative strategies to reduce emissions of SO_2 from point sources in Wayne County, Michigan. Point source emissions of SO_2 were identified in Chapter 3 as having a disproportionate impact on disadvantaged communities in the study area. Because a portion of the study area is designated as non-attainment for the SO_2 National Ambient Air Quality Standard (NAAQS), the Michigan Department of Environmental Quality (MDEQ) has developed a State Implementation Plan (SIP) to achieve compliance with the standard; this analysis is therefore timely and was able to make comparisons between MDEQ's proposed strategy and alternatives focused on minimizing health impacts. SO_2 continues to have a substantial impact on the health of the study area population, particularly among children and Hispanic or Latino populations. Its impact is especially important given the high rates of asthma in southwest Detroit relative to the state of Michigan (DeGuire et al. 2016). AQM strategies that focus on emission sources with the highest health impacts per ton of pollutant emitted provided the greatest health benefit per ton of pollutant reduced; these strategies also reduced the inequality of attributable health risks. In contrast, strategies targeting the larger emitters increased inequalities in attributable risk and provided minimal health benefits. This finding is supported by national scale analyses of power plants (Levy et al. 2007). The results also suggested that the strategy outlined by MDEQ's SIP (MDEQ 2016), which targets several large sources, will lead to only modest reductions in SO_2-related health burdens and will do little to alleviate disparities associated with SO_2 emissions.

Chapter 5, the second to address Specific Aim 3, used the quantitative HIA framework, an indoor air quality model, and a Monte Carlo analysis to estimate the potential health benefits of installing filters in homes and schools to reduce exposures to $PM_{2.5}$, which was shown in Chapter 3 to be a primary driver of adverse health impacts in the study area. The results suggest installing more efficient filters in homes and schools could improve asthma-related health outcomes in Detroit children. Reasonably efficient filters (e.g., rated MERV 8 to 14) installed in schools could reduce annual asthma burdens 8 to 15% (17 to 30% during the school year). Costs of using these filters in classrooms are low (less than $5 per student per school year, or $16-32 per student with asthma per school year) compared to annual benefits ($19 to $164 per child with asthma per school year). Filters installed in homes can further reduce the number of asthma symptom-days; reductions in annual asthma burdens during the year are estimated to range from 11 to 16% with household costs from $151 to $175 per house with a forced air system per year and $494 per house per year for stand-alone filters. Overall, the average cost of filters in homes ($202 to 222 per child with asthma per year) is similar to the annual benefits ($118 to $182). Unfortunately, the higher costs of filters in some homes, particularly those without forced-air systems, may be prohibitive for many families. The analysis of filters considered only asthma-related health impacts on children due to exposures to $PM_{2.5}$ from outdoor sources. The benefits of filters would be higher if impacts of other pollutants, e.g., pet dander or pollen, were considered, and if impacts of $PM_{2.5}$ on adult health were included, e.g., mortality or hospitalizations for cardiopulmonary diseases.

Tradeoffs of selected control strategies for Detroit and surrounding cities

The strategies to reduce health impacts from ambient air pollution examined in this dissertation, point source controls and filters in school and homes, have tradeoffs that should be considered when deciding on an appropriate strategy for Detroit and the adjacent cities included in this study. Point source controls reduce emissions at the source and often control several pollutants simultaneously, e.g., "wet scrubbers" are a type of flue gas desulfurization system that can remove SO_2 and $PM_{2.5}$ from waste streams (Schnelle and Brown 2001). Lower emissions of certain pollutants can also reduce other pollutants, e.g., reducing SO_2 emissions reduces secondary formation of $PM_{2.5}$ (e.g., sulfate particles). Point source controls may benefit many people at once, and controls do not require individuals to modify their behaviors, which has had limited success as an AQM strategy (NRC 2004). Importantly, the cost of point source controls fall on the polluter, not the exposed population. Despite these advantages and the potential public health benefits, point source controls have limitations for the study area. First, the point source controls examined in Chapter 4 do not address the regional component of ambient pollutant concentrations, which was shown in Chapter 3 to be responsible for much of the health burden in the area. Second, for many facilities, e.g., the electricity generating stations owned by DTE Energy, control costs are likely to be passed to consumers through rate hikes. Third, many facilities in the area are "grandfathered," are not required to install addition controls, and will resist doing so. The SO_2 SIP development process demonstrates the difficulty of imposing additional controls on older facilities, e.g., none of the facilities that burn coal (the major source of SO_2) in the area will be required to install SO_2 scrubbers even when the area is in non-attainment of the standard (MDEQ 2016). Existing facilities would require major modifications to add scrubbers and other controls (US EPA 2014a), but such modifications are unlikely given the age of many of the facilities. Fourth, the marginal benefits of upgraded controls may be limited as many facilities already use control technologies, e.g., baghouses to control $PM_{2.5}$, or employ tall stacks to aid dispersion. Finally, a regulation-averse environment makes the likelihood of going beyond legal requirements rather limited.

The second strategy examined, the use of filters in schools and homes, also involves important tradeoffs. Increasing filter use and using more efficient filters have several advantages. Filters address exposures in indoor environments where people spend most of their time (Klepeis et al. 2001) and can be particularly effective for reducing exposures in spaces where people congregate, e.g., schools and workplaces (Chapter 5). Filters address $PM_{2.5}$ exposures regardless of source, which is important given the large contribution of regional transport to local $PM_{2.5}$ concentrations in Detroit (Milando et al. 2016). Similarly, they can remove multiple indoor pollutants at once, and thus may confer additional health benefits beyond those quantified in this dissertation, e.g., reduced respiratory infections as a result of removing respiratory viruses in homes (Brown et al. 2014). However, there are drawbacks to depending on filters as an intervention. First, their cost is, in most cases, the responsibility of the building occupant, and although filters may have low marginal operating costs, users may perceive the cost to be too high, especially for stand-alone filters (Batterman et al. 2013). Second, their effectiveness depends on their use (or duty cycle), which can be low for some users (Batterman et al. 2013), and on the "tightness" of the building envelope and ventilation conditions, e.g., opened windows (e.g., to cool the house) will reduce filter effectiveness (Du et al. 2011). Third, filters require regular maintenance, i.e., quarterly replacement. Overall, filters can be an effective intervention for residents living in the study area, but successful implementation should include educational information on best practices for building managers and residents, e.g., keeping windows closed and regularly changing out filters, as well as an understanding that the cost of filters is low compared to avoided health care costs. Education and outreach efforts should also include information on weatherization programs, which can improve building tightness and increase filter efficiencies.

Using HIA and inequality metrics to guide local decision-making

A primary goal of this dissertation was to demonstrate how quantitative health impact and inequality metrics can generate information relevant to decision makers. Although the application focused primarily on Detroit and the adjacent “downriver” communities with high potential for health impacts and thus results may be area-specific, the methods developed in this dissertation could be applied in other urban settings to generate important data for decision-making, specifically, helping to transition AQM strategies from being NAAQS compliance-oriented to being both more protective of public health and more equitable.

This dissertation has demonstrated the value of using finely-resolved, place-based HIA methods tailored to a specific decision-making context, including the scope of the decision. Chapters 3 and 5 restricted the scope of the analysis to the municipal boundaries of the included cities in order to align the analysis with the authority of local decision makers and to help identify priority areas for public health action. Analyses in Chapter 3 identified specific sections of the city, e.g., southwest Detroit, and population subgroups, e.g., Hispanic/Latino and low-income residents, that are disproportionately impacted. In contrast, Chapter 4 expanded the scope of the non-attainment area (MDEQ 2016) to ensure that the health impacts of SO_2 (identified in Chapter 3) were captured in the analysis of alternatives. Sensitivity results in these two chapters emphasize that study boundaries should be chosen deliberately and with regard to the decision-making context; potential uncertainties arising from the selection of study boundaries need to be clearly communicated to decision-makers (Mesa-Frias et al. 2013).

The boundaries of the study area affect the interpretation of the inequality assessment, especially for the concentration index (CI), which compares health burdens across census blocks ranked by their degree of social advantage. In this application, we are comparing health burdens across census blocks within the study area, the boundary of which was selected to facilitate a finely resolved analysis at the intra-urban scale (Chapter 3). The study area (including Detroit and the surrounding cities) is predominantly minority (75.6% are persons of color) and 36.8% of residents live below the poverty level. This differs from the tri-county Detroit Metropolitan area, where 50, 26, and 18% of residents in Wayne County (including the study area), Oakland County, and Macomb County are persons of color and 25, 10, and 13% of residents live below the poverty line, respectively (US Census Bureau, 2014). In this application, with a narrowly defined study boundary, the inequality metrics are useful for identifying the most heavily impacted groups in the study area and determining if these heavily impacted populations are "environmental justice" communities, but they are not useful for comparing socially advantaged and disadvantaged communities. Such an analysis would require a much broader study area (e.g., Sadd et al. 2011; Schulz et al. 2016; Su et al. 2009, 2013) that is beyond the scope of the present work. Caution should be used when interpreting the results of the inequality assessments to avoid the perception that some groups with known health disparities do not face environmental justice issues.

Highly resolved estimates of health burdens and disproportionate impacts can help to prioritize public health actions aimed at reducing air pollutant exposures. For example, the results of Chapter 3 indicated mobile sources contributed to disproportionate health burdens, particularly among the areas of the city with the highest degrees of poverty. This finding could be used to prioritize low-income areas for programs to expand tree canopy cover and vegetative buffers. Similarly, Chapter 5 demonstrated the benefits of using filters to reduce indoor exposures to $PM_{2.5}$ from outdoor sources. Benefits are potentially large for schools, and likely highest when using filters in near-road schools. Such information would be useful to parent or school groups focused on improving environmental conditions within schools. Targeting highly impacted areas first, e.g., low-income neighborhoods or schools near major roads, when designing public health strategies increases the likelihood of positive outcomes for residents and can generate key evidence to support public health decision making (Brownson et al. 2009).

Decision makers may use the health and inequality data generated by HIAs to prioritize AQM strategies. Ideally, public health interventions would be implemented so that the entire population benefits and health disparities are eliminated. More realistically, tradeoffs between alternatives will need to be made because of limitations in resources and in the available legal and regulatory instruments. Decision-makers may prioritize strategies that produce the largest number of health benefits overall, i.e., focusing on efficiency or utility, or they could prioritize strategies that provide the greatest benefits to those who are worst-off, i.e., focusing on equity or environmental justice (Adger et al. 2003). Other policy considerations, e.g., economic or political constraints, are also important. Quantitative methods that include health and inequality metrics can be used to elevate public health concerns to receive the same level of attention as other decision-making criteria. As an example, Chapter 4 compares the MDEQ SIP strategy to an alternative that meets health benefit goals. US EPA guidance requires that the SIP strategy be designed to ensure concentrations in the non-attainment area will not exceed the NAAQS (US EPA 2005). This approach assumes that meeting the NAAQS is sufficient to protect public health. As discussed in Chapter 1, meeting the NAAQS may not be sufficient to fully protect public health for a number of reasons, including the vulnerability of exposed populations. Using a concentration criterion when developing the SIP favors strategies that reduce emissions at the largest sources in the area, which typically have tall stacks to increase dispersion of emissions (MDEQ 2016). The HIA methods used in Chapter 4 reveal that for Detroit, it is the smaller sources with shorter stacks located closer to residential areas that have the greatest impacts per ton emitted; reducing emissions at these smaller facilities first can have greater health benefits while still meeting the NAAQS attainment criterion used by US EPA. Increased costs of emissions controls at smaller facilities may be offset by the greater gains in public health. Such comparisons could not be made without the quantitative HIA methods used in Chapter 4. While a comprehensive analysis of preferred approaches for prioritizing AQM strategies using health and inequality data is beyond the present scope, this work makes clear that the methods for quantifying health and inequality impacts allow decision makers to consider tradeoffs between health and equity and other decision criteria when evaluating alternatives.

Using HIA and inequality metrics to improve AQM policy at the state or national level

The results of this dissertation (and similar analyses carried out in other urban areas) could also be used to support policy changes at the state and national levels to advance environmental justice (EJ) goals. In the EJ 2020 Action Plan, US EPA emphasized its commitment to the fair treatment for all groups under environmental laws, and explained that fair treatment refers to "not only consideration of how burdens are distributed across all populations, but the distribution of benefits as well" (US EPA 2016a p. 55). US EPA recently released a technical guidance document for including EJ in regulatory actions that called for quantitative assessments to complement other US EPA assessments in the regulatory process (US EPA 2016c). As suggested in Chapter 4, the current process for designing and implementing SIPs that focuses on attaining NAAQS compliance in a sparse network of air quality monitors may be insufficient to meet US EPA's goal of fair treatment for all groups, and that although all groups experience a decrease in attributable health burden under the SIP strategy, inequalities in health burdens remain (Table 4.8). Such inequities are only evident when health and inequality metrics are included in the assessment of alternatives.

Currently, there is no regulatory framework for including health or inequality metrics when designing AQM strategies for NAAQS attainment; US EPA guidance only requires states demonstrate that the strategy will reduce ambient concentrations to meet the standard using air quality models (US EPA 2005). However, MDEQ staff have expressed interest in building cross-agency capacity to conduct health impact and inequality assessments. Much of the data needed to conduct the analyses in Chapter 4 are already available to state environmental agencies, e.g., air quality data, dispersion models, and quantitative HIA tools such as BenMAP. Requiring their use as part of the regulatory process would increase the analytical burden on state agencies, but the potential gains for public health and EJ could be large.

Another area where HIAs could affect policy change is the issuance of air permits and the determination of penalties for permit violations. Rule 203 of the Michigan Air Pollution Control Rules requires that permit applicants demonstrate their emissions will not have an "unacceptable air quality impact in relation to all federal, state, and local air quality standards," but does not require consideration of health or cumulative impacts (Michigan Administrative Code R 336.1201 - 336.1299). Likewise, the rules for setting penalties for permit violations do not consider health impacts. As an example, in a recent response to comments on a consent order issued in early 2017 for violations at the Detroit incinerator, MDEQ acknowledged the cumulative health impacts experienced by residents living near the incinerator, but stated that health impacts resulting from emissions violations at the incinerator are not expected because health-protective NAAQS are not exceeded (MDEQ 2017).[2] However, the results from Chapter 3 suggest health impacts for nearby residents can occur at concentrations below the NAAQS, especially among vulnerable populations. US EPA's penalty guidance, last updated in 1991, does not take in to account attributable health impacts when determining penalties for permit violations, nor does it consider EJ concerns (US EPA 1991). Including such considerations through new or revised rules could lead to denied permits for some industrial facilities near residential areas or higher penalties that may serve as stronger deterrents to permit violations, but would require evidence on how emissions from specific local sources affect public health and contribute to cumulative impacts. Such data are not currently available for most urban areas.

Although the results of this dissertation demonstrate the value of quantitative health and inequality metrics when selecting strategies to meet standards or reduce exposures, their role in rulemaking remains unclear. US EPA's EJ 2020 Action Agenda identifies institutionalizing EJ in rulemaking as an agency priority, and emphasizes that EJ should be "appropriately analyzed, considered and addressed in EPA rules with potential environmental justice concerns" (US EPA 2016a p. 13). The Technical Guidance document states a preference for quantitative metrics for EJ analyses (US EPA 2016c). The quantitative metrics used in this work, e.g., disability-adjusted life years, the Atkinson Index, and the Concentration Index, could be used to support US EPA's

[2] The comment that fostered this response from MDEQ cited an analysis included in the CAPHE Resource Manual that was performed using the methods described in Chapters 3 and 4 of this dissertation. Impacts attributable to $PM_{2.5}$, SO_2 and NO_2 emissions from the largest point sources in the area were estimated, including the incinerator operated by Detroit Renewable Power. The CAPHE Public Health Action Plan Resource Manual is available online: http://caphedetroit.sph.umich.edu/resource-manual-cover-page-with-full-manual/

goal. However, there are some challenges to using these metrics when setting standards at the national level. First, health impact metrics, e.g., attributable cases and monetized impacts, are already included in Risk and Exposure Assessments (REAs) done as part of the rulemaking process. However, REAs, which are not required, only quantify exposures and impacts for current air quality and changes in air quality require to meet (but not exceed) the proposed standard (Sacks et al. 2015), do not include cumulative impacts from other environmental and social stressors, and are typically done at very coarse spatial resolution, e.g., county level, due to data limitations and computational burdens (e.g., US EPA 2012, 2014b, 2016b). Such assessments smooth gradients in vulnerability that affect impact estimates. Second, as demonstrated by sensitivity analyses in Chapter 3, the interpretation of inequality metrics depends on its spatial scale. National or regional analyses of inequality in exposures or impacts may draw very different conclusions than local-scale analyses. Third, as discussed in Chapter 3, there are no clear standards or thresholds for inequality metrics, and small differences between groups or alternatives may not be meaningful. More work is needed to understand how the metrics used in this dissertation could facilitate EJ analyses when setting NAAQS or other national rules.

Limitations and challenges to using HIA at the local scale

Although this dissertation has demonstrated the usefulness of quantitative HIA methods to support local decision-making, there are important barriers to implementation of such practices that should be addressed. There are important questions regarding who should be in charge of the HIA for a specific environmental decision. HIAs initiated by community groups can readily incorporate local knowledge and experiences (Corburn 2003), but may lack the technical rigor expected by decision makers (Harris et al. 2014). One way to increase community capacity and the relevance of community-led HIAs is to offer technical assistance to community groups (Freudenberg et al. 2011). On the other hand, HIAs initiated by agencies or consultants may rely too heavily on quantitative analyses, be overly focused on single pollutants and negative health impacts, and fail to properly engage stakeholders in the process (Carmichael et al. 2012; O'Connell and Hurley 2009). For HIAs to be successful in influencing decisions at the local level, there needs to be institutional support for their use (Ahmad et al. 2008). Institutions should establish shared definitions of health and health impacts, and should work to include HIAs in the early stages of the decision-making process when changes to proposals are feasible (Carmichael et al. 2012; Harris et al. 2014). Cross-agency collaborations and partnerships with community-based organizations will be important for developing appropriate frameworks for using HIAs at the local level. Comprehensive HIAs that use quantitative and qualitative methods are time and resource intensive, and addressing these barriers at the local scale is important to making sure that efforts are not wasted.

This dissertation has incorporated local data when available into the quantitative HIA methods, but there are still some key data gaps that can be addressed. At the local (i.e., intra-urban) scale, quantitative HIAs are often limited by a lack of optimal datasets (Hubbell et al. 2009). For the study area used in this dissertation, spatially-resolved baseline rates for some health outcomes were not available, e.g., asthma symptom days or school absences, because these data are not routinely collected as part of public health surveillance programs. Local scale HIAs would benefit from comprehensive and spatially-resolved exposure data addressing multiple environmental hazards, e.g., criteria pollutants, air toxics, water contaminants, noise, and social stressors, e.g., lack of access to health care or nutritious food. This dissertation focused on criteria pollutants and examined some dimensions of susceptibility and vulnerability, but other environmental and social hazards can contribute to health burdens and contribute to health disparities. Census data captures some of the social hazards, e.g., vulnerability due to poverty, but other neighborhood characteristics should be explored. Developing the types of comprehensive datasets necessary for local-scale HIAs will require cooperative efforts across agencies, universities, and non-governmental organizations. As HIAs gain traction as local decision support tools, mechanisms for funding the types of data collection and collaboration needed should be identified.

HIAs are often conducted with the intent of informing decision-makers about alternatives for policies or programs (Harris-Roxas and Harris 2011). In this capacity, HIA results will be communicated to stakeholders without technical expertise in environmental science, mathematical modeling, or public health. Stakeholders, and in particular policy makers, need information that is readily absorbed, and decision-makers have little time to devote to reading long reports on health impacts (Sanderson et al. 2006). Thus, strategies for communicating results to a wide range of audiences are needed.

As detailed elsewhere in this dissertation, HIA results are inherently uncertain, and this uncertainty needs to be communicated to decision-makers. Decision makers appreciate and can reasonably interpret quantitative expressions of uncertainty, and including uncertainty in the results respects the need of decision makers to act with a degree of uncertainty (Fischhoff and Davis 2014). Additional sources of uncertainty that cannot be quantified also should be communicated to decision-makers. HIA practitioners should communicate to decision-makers how assumptions in the methodology may affect results, e.g., using national or state-level outcome rates for local-level HIAs has implications for interpreting the results that need to be addressed (Hubbell et al. 2009). Practitioners also need to communicate the framing assumptions, e.g., which exposures were excluded or how study boundaries and resolution were determined, and how this limits interpretation (Briggs et al. 2009). Successful strategies for communicating uncertain HIA results in a way that elevates health to the status of other important decision criteria (e.g., cost), need to be identified, especially in a contentious economic and political climate.

Future work

This dissertation focused on HIA methods applied at the intra-urban scale. The results are limited to a single year and include only quantitative estimates of impacts from four criteria pollutants. Some potential directions for future work are discussed below.

First, longitudinal studies of the health burden for the city of Detroit (and other urban areas) are needed. Regular assessments of the burden of disease attributable to environmental and other factors will allow for the detection of important trends over time and assess whether any efforts to reduce burdens and inequality are working. To this end, frequently updated HIA databases are needed. Improvements in exposure assessment and epidemiological techniques are starting to reveal health effects below current standards (Di et al. 2017; Schwartz et al. 2017; Shi et al. 2016), and concentration-response functions should be reviewed periodically to ensure the most relevant values are used. Similarly, new health outcomes should be added to the assessment as evidence of causality is strengthened to fully capture the attributable burden. Other elements of the analysis that should be updated frequently include populations, baseline health rates, and indicators of vulnerability. Future assessments should also address some of the limitations of this work, including the lack of population and baseline risk projections for outcomes with long latency periods, e.g., mortality due to $PM_{2.5}$ exposures (Flachs et al. 2013), and the omission of time-activity patterns that influence exposures and health impacts (Tchepel and Dias 2011). As MDEQ expands the monitoring network near Detroit to include a monitor in the 48217 ZIP code[3] and three monitors near the new Gordie Howe International Bridge project,[4] new data should be incorporated into the exposure assessment methods. In other urban areas that have denser monitoring networks and perhaps greater homogeneity of emissions, geospatial techniques such as kriging might be utilized to make better use of monitoring data.

Second, additional studies are necessary to confirm the benefits of point source controls and increased use of filters estimated in Chapters 4 and 5. The analyses in Chapters 4 and 5 use models to estimate the benefits of reduced emissions or exposures to criteria pollutants that

[3] *DEQ to Conduct Air Monitoring in Detroit Neighborhood*. Press Release. August 15, 2016. Available: http://www.michigan.gov/deq/0,4561,7-135-3308-391433--,00.html

[4] MSHDA awards grant to MDEQ for air quality monitoring in Detroit neighborhoods. Press Release. June 7, 2017.

involve many assumptions. Future work should examine the effectiveness of emissions controls or filters of reducing exposure and health impacts. Such work may be more feasible for filters than point source controls, e.g., prior work in Detroit has focused on filters as an intervention to reduce $PM_{2.5}$ exposures in homes of children with asthma (Batterman et al. 2012), but studies of point source controls could take advantage of SIP implementation or other "natural" experiments. Future studies of air quality management strategies should focus on pre- and post-intervention data collection at the finest spatial resolution feasible, including ambient concentration, personal exposures, and the incidence of asthma-related health outcomes. Future studies should also work to identify co-benefits of interventions, e.g., additional health benefits from reduced secondary $PM_{2.5}$ resulting from lower SO_2 emissions or reductions in other indoor pollutants from increased use of filters.

Third, more work is needed on the usefulness of quantitative HIA methods for EJ and cumulative impact studies. Chapter 3 demonstrated that concentrations are a poor proxy for health burdens at the intra-urban level and that inequality metrics were higher for health burdens than concentrations. However, the analysis did not consider other environmental and social stressors that contribute to cumulative impacts, and it remains unclear how using health burdens in a cumulative impacts study would affect interpretation of the overall cumulative impact assessment results. Future work should investigate the usefulness of health impact assessments in cumulative impact studies at various spatial scales (e.g., intra-urban, regional, or state-wide).

Fourth, it will be important to assess if and how results of quantitative impact assessments influence public policy around air quality in Detroit, MI. Within the policy context, decision makers have to decide how to protect and promote public health and reduce inequalities using the evidence available to them (Tannahill and Douglas 2014). Evidence regarding the ability of HIAs to influence decision makers is mixed (Bourcier et al. 2015; Dannenberg 2016). Chapter 2 discusses how health impact metrics might influence decision makers, and it will be important to determine if presenting these metrics encourages decision makers to consider health with the same weight as other important policy drivers, e.g., economic impacts. Differences in perceptions of "levels" and use of evidence may be important in determining the impact of HIA results in for decision making because policy makers tend to look for evidence to support their agendas (Choi et al. 2005). Future work should determine whether HIA results can influence decision-makers who have not been primarily concerned with health outcomes.

Finally, future work should identify strategies for incorporating qualitative assessments of health impacts in AQM HIAs. Most AQM HIAs focus on the quantitative impacts of pollutant exposures, in large part because tools for automating quantitative assessments are available (Anenberg et al. 2015; reviewed in Chapters 2 and 3). As discussed in Chapter 3, there are important health effects from sources of air pollution that cannot be reliably quantified, e.g., mental health impacts of living near industrial sources or exposure to noise from busy roadways (Basner et al. 2014; Bluhm et al. 2007; Downey and Willigen 2005). This is particularly important at the local scale where decisions are made about specific projects or policies, e.g., building a new bridge or expanding a highway, that directly impact communities. Information about community perceptions of risk, health effects, and inequality is also important for environmental decision making (Wright et al. 2005). Future work should focus on developing a framework for including both quantitative and qualitative HIA results in AQM decision-making processes, as well as increasing the capacity for communities to participate. All of this will help to ensure that health data are appropriately considered, particularly at the local level (Chadderton et al. 2013; Freudenberg et al. 2011; Harris et al. 2014)

Overall conclusions

This dissertation demonstrated the value of quantitative health impact assessment methods for AQM at the urban scale. Health and inequality metrics, when tailored to the local setting, can provide useful information on the health burden and inequalities associated with ambient air pollutant exposures. This information can be translated into public health policies and interventions aimed at reducing these health burdens in a more equitable way.

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