 DOI: 10.1111/risa.12540

Survey of Ambient Air Pollution Health Risk Assessment Tools

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Designing air quality policies that improve public health can benefit from information about air pollution health risks and impacts, which include respiratory and cardiovascular diseases and premature death. Several computer-based tools help automate air pollution health impact assessments and are being used for a variety of contexts. Expanding information gathered for a May 2014 World Health Organization expert meeting, we survey 12 multinational air pollution health impact assessment tools, categorize them according to key technical and operational characteristics, and identify limitations and challenges. Key characteristics include spatial resolution, pollutants and health effect outcomes evaluated, and method for characterizing population exposure, as well as tool format, accessibility, complexity, and degree of peer review and application in policy contexts. While many of the tools use common data sources for concentration-response associations, population, and baseline mortality rates, they vary in the exposure information source, format, and degree of technical complexity. We find that there is an important tradeoff between technical refinement and accessibility for a broad range of applications. Analysts should apply tools that provide the appropriate geographic scope, resolution, and maximum degree of technical rigor for the intended assessment, within resources constraints. A systematic intercomparison of the tools' inputs, assumptions, calculations, and results would be helpful to determine the appropriateness of each for different types of assessment. Future work would benefit from accounting for multiple uncertainty sources and integrating ambient air pollution health impact assessment tools with those addressing other related health risks (e.g., smoking, indoor pollution, climate change, vehicle accidents, physical activity).

KEY WORDS: Air pollution; health impact assessment tools; mortality; ozone; particulate matter

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1. INTRODUCTION

Decades of toxicological, clinical, and epidemiological research demonstrate significant associations between exposure to ambient air pollution and deleterious human health effects, including respiratory disease, cardiovascular disease, and premature death.(1–4) Air pollution is a mixture of components, including fine particles ($PM_{2.5}$), ground-level ozone (O_3), oxides of nitrogen (NO_x), and oxides of sulfur (SO_x). The health effects of individual air pollutants have been reviewed in detail to support the setting of ambient air quality guidelines by the World Health Organization(5) and national standards, such as the U.S. National Ambient Air Quality Standards.(6–9) For example, extensive reviews by the U.S. EPA conclude that long-term exposure to $PM_{2.5}$ is associated with premature death, heart attacks, irregular heartbeat, and respiratory symptoms such as aggravated asthma and decreased lung function,(7) that short-term exposure to O_3 is associated with respiratory effects, cardiovascular effects, and premature all-cause mortality, and that long-term exposure to O_3 is associated with respiratory effects, including some evidence for association with premature respiratory mortality.(8) Beyond individual pollutants, research is also increasingly demonstrating the health effects of air pollution mixtures, such as from biomass smoke or traffic.(10–12) In addition, studies show that some areas have a confluence of health risks from multiple pollutants, and therefore a multi-pollutant air quality management approach may be efficient at mitigating those risks.(13,14)

While the majority of epidemiological research has been conducted in North America and Europe, insofar as it is available, evidence suggests that the associations between air pollutants and health effects are relatively consistent around the world.(10) However, as some studies indicate a leveling off of risk at high $PM_{2.5}$ concentrations found in many developing countries, researchers have leveraged epidemiological studies of ambient $PM_{2.5}$, typically higher levels of indoor air pollution in developing countries where solid fuel is used for cooking and home heating, and very high particulate exposure levels from cigarette smoking to develop "integrated exposure response" (IER) curves.(15) Because the IER curves were developed from concentration-response data taken from around the world, among a variety of populations, and across a range of exposure concentrations including high $PM_{2.5}$ concentrations, they may be more broadly applicable globally than concentration-response relationships from epidemiology studies in one location among a single population at low concentrations only. The IER approach was used by the Global Burden of Disease project to calculate that approximately 3.2 million and 150,000 premature deaths globally in 2010 were attributable to ambient $PM_{2.5}$ and ozone, respectively.(16) In addition, household air pollution was associated with an estimated 4 million premature deaths globally in 2010 (approximately 0.5 million overlapping with the estimated ambient particulate matter deaths), making it the fourth worst health risk factor after high blood pressure, smoking, and alcohol use. Ambient $PM_{2.5}$, not including ambient ozone, was the seventh worst health risk factor globally based on associated premature deaths.

Driven by the extensive body of literature demonstrating their health effects, ambient concentrations of particulate matter and ozone are now regulated in many countries. Setting these regulations at levels sufficient to protect public health typically makes use of a variety of technical inputs, including estimates of the total population health burden posed by the pollutants at current concentrations as well as the health benefits of reducing air pollution levels. There are a number of variants to these two inputs—for example, analysts may wish to understand the historical trend in the human health burden of air pollution caused by a specific polluting sector or experienced by a certain subpopulation such as children. Over the last decade, governmental, intergovernmental, and nongovernmental entities have invested in tools that are better able to meet this growing demand for more specific and timely information regarding health impacts associated with exposure to air pollutants. For example, the U.S. Environmental Protection Agency developed the Environmental Benefits Mapping and Analysis Program (BenMAP-CE) in part to help fulfill requirements by the Office of Management and Budget and the Clean Air Act to characterize the benefits and costs of U.S. air pollution regulations.(17,18) Other countries and intergovernmental organizations such as the World Health Organization and World Bank have invested in similar tools to quantify air-pollution-related health impacts for a variety of purposes.(19–21)

Health impact and health burden assessments depend strongly on the evidence available from air pollution epidemiology and exposure science. Recent advances in these two disciplines have enabled health impact assessments to combine findings from atmospheric science and epidemiology, allowing analysts to quantify an increasing number of health outcomes in far greater detail than was previously possible. Over the last decades, air pollution epidemiology has characterized risks of certain health outcomes in a population exposed to a higher level of air pollution relative to a population exposed to less air pollution ("relative risk"). Many determinants of health, including socioeconomic status and other risk factors such as smoking, affect the same health outcomes as does outdoor air pollution, and may covary with pollution. Epidemiology studies attempt to isolate the effect of air pollution by controlling for such confounders, either by design (as in studies of short-term exposure) or in the analysis (as in studies of long-term exposure and mortality). Thus, the resulting relative risk estimates for air pollution may be considered to be largely independent of all the confounders included in the study's model (other unknown confounders may not have been included and could thus still influence the results). Building from this base of air pollution relative risk estimates, quantitative air pollution health impact assessments can now be performed at various scales and resolutions for many air pollutants, including $PM_{2.5}$, O_3, NO_x, and SO_x.

A variety of studies have now quantified health impacts associated with these air pollutants at global,[16,22–28] regional,[29–32] national,[17,33–37] and local scales.[13,17,18,38–43] Quantification of changes in health effects due to various emission reduction scenarios has been the basis of analysis supporting air quality policy development of the European Union[44,45] and the United States,[46] in addition to other countries. Results of these assessments are often reported in numbers of deaths and disease cases, years of life years lost (YLL), disability-adjusted life years (DALYs), or change in life expectancy attributable to total air pollution concentrations or a change in air pollution concentrations.

Using computer programs, or tools, to automate the procedure for calculating the incidence or prevalence of air-pollution-related health impacts offers several advantages: simplicity (lowering the barrier of entry for new analysts to conduct assessments), consistency, comparability among assessments, and quality assurance. However, as discussed later, there may be associated disadvantages also, especially if the analyst is unaware of the detailed assumptions built into the tool and/or of their importance in particular applications. Many of these available air pollution health impact assessment tools use the attributable fraction approach to quantifying health impacts, wherein epidemiology-derived concentration-response associations and population-level exposure estimates are used to determine the portion of cases of a particular health effect that may be attributable to air pollution in a particular time period. This method requires information about air pollution concentration levels, the relationship between concentrations and health outcomes (which could be provided by systematic analysis of studies done outside of the assessed population,[47] or by a shrunken estimate analysis combining a robust meta-analytical risk with a local one when available[48]), and the characteristics of the populations exposed, including their baseline health status, age, and location (Fig. 1).

Air pollution health risk assessment tools are typically preloaded with health and demographic data and concentration-response associations, and some allow for user-specified inputs. Some of these tools also have built-in air pollution exposure information connecting emissions to the exposure metric, requiring users to input only information about emission changes; others read in user-specified exposure estimates. To determine the appropriate air pollution health impact assessment tool, data sets, and context for interpreting results, analyses typically begin with key demographic and economic data for the relevant geographic area and population, including per capita income, health-care delivery systems, prevalence of smoking, climate (including use of air conditioning), use of combustion sources indoors (e.g., for cooking and heating), the nature of the air quality monitoring system, and major health indices. The availability of high-quality data sets for these parameters varies by context, including country and spatial scale.

This article reviews 12 air pollution health impact assessment tools that are currently available, categorizes the tools according to key technical and operational characteristics for different assessment contexts, and identifies information gaps relevant for future work. These tools, often designed for a particular type of assessment context, vary in methodological approach, technical complexity, geographical scope, resolution, and other aspects. Here we define "assessment context" as the parameters of the intended analysis, including its purpose (e.g., is it being used to inform the setting of a policy or as a nonregulatory communication tool), the geographic area of interest (e.g., a single city, a country, a region of the world, or global), and the type of information it seeks to provide (e.g., health burden of current air pollution levels, health benefits of reduced air pollution levels, health benefits of reduced air

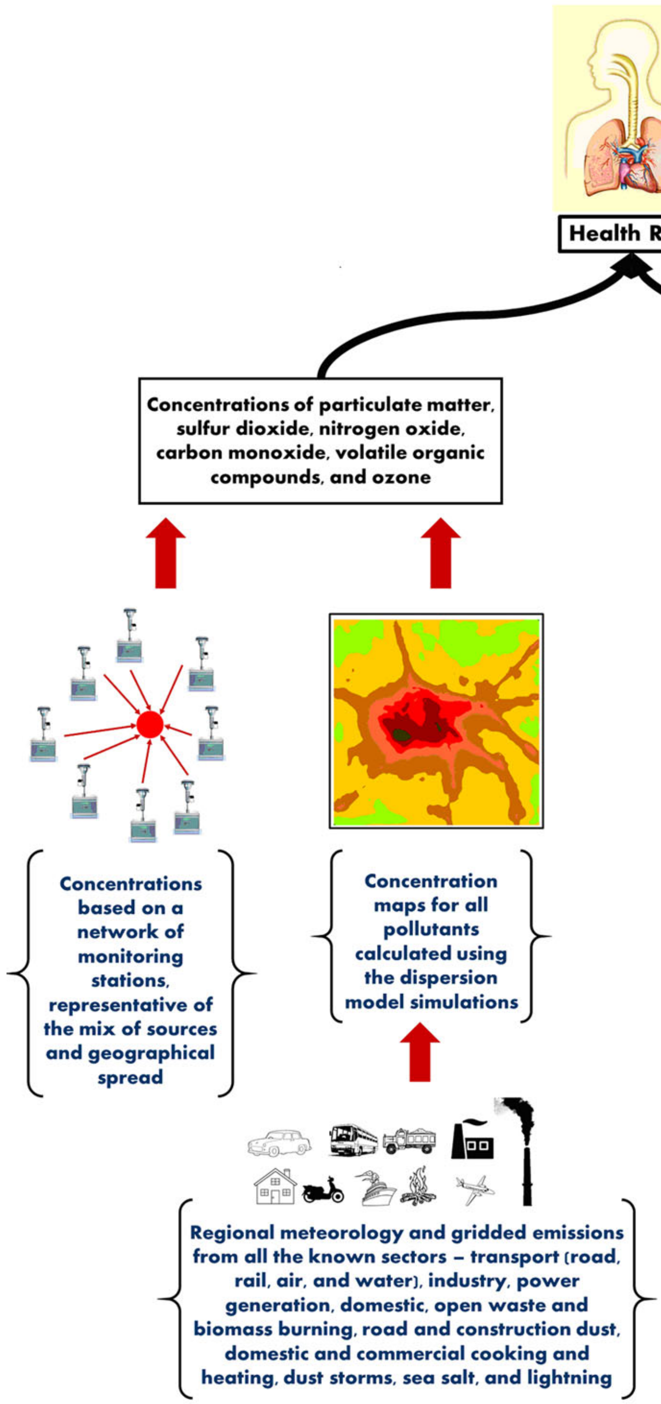

Fig. 1. Schematic of air pollution health impact assessment method and typical data inputs.

pollution emissions). This article is the first to survey available air pollution health risk assessment tools to begin to understand the spectrum of methods and assumptions used. To date, no study has systematically compared the results across many tools (e.g., by comparing results from various tools using a consistent set of analyses), as has been done for air quality models that are often used as inputs to health impact assessment tools.[49–51] In general, air quality models have been reported on in the peer-reviewed literature in far greater detail compared with air pollution health impact assessment tools, allowing for the community of researchers to understand their inputs, processes, and outputs. Given the relative paucity of public information about air pollution health impact assessment tools to date, this first survey of the available tools will enable comparisons across the tools to be made in the future.

Tools that as currently configured apply to a single country are summarized in the Supplemental Material but are not synthesized in this article due to their limited geographical scope. This article does not address methods to assign an economic value to health outcomes, though many of the tools reviewed include that capability. In addition, the tools reviewed here focus on ambient air pollution, as methods and tools for quantifying household air pollution health impacts are in an earlier stage of development.

2. METHODS

This article was first developed as a white paper for input to the World Health Organization (WHO) Expert Meeting on Health Risk Assessment held in Bonn, Germany, May 12–13, 2014, and was subsequently revised and expanded with additional information.[52] To identify the universe of relevant tools that are currently available and in use, the steering committee for the expert meeting was asked to submit the names of air pollution health risk assessment tools that their organizations have developed, used, or know others have used. The steering committee consisted of scientists and policy analysts from WHO, academia, governments, and the World Bank. The developers of the identified tools were then contacted to determine interest in participating in this survey. Some of the tool developers submitted additional tools for inclusion in the white paper. This process yielded 20 tools used to quantify ambient air pollution health risks at various geographic scales. We then performed an informal review of the peer-reviewed literature published in English using the following search terms together in Google Scholar: "air pollution," "health impact" or "health risk," and "tool." This process did not uncover any additional tools currently in use that also met our criterion of encompassing multiple countries, though there may be additional tools that meet our criteria that have not been described as a tool (considered here as stand-alone computer programs that are packaged for distribution and use by analysts other than the developers) in an English-language peer-reviewed journal article.

The tool developers were then asked to respond to a list of survey questions on technical and operational aspects of their tool (see Supplemental Material). The survey questions covered a broad range of characteristics, such as the pollutants included, geographical scope, spatial resolution, temporal resolution, exposure metric, exposure information source, health outcomes, concentration-response associations, population and baseline incidence and/or prevalence data sources, format of the tool, whether it is opensource or proprietary, how to obtain the tool, whether training materials exist, whether the tool has been peer reviewed, whether the tool has been used to support an air quality policy, and the developing institution and contact person. Of the 20 tools, information was submitted in response to the survey for 17.

The 17 tools for which information was provided were categorized by geographical scope according to the tool's preconfiguration. Geographical scope is often the first factor an analyst must consider in selecting a tool for a particular assessment. Geographic scope is defined as the spatial coverage or extent of the tool as currently configured, and is distinct from spatial resolution. For example, a tool with global scope may have a national resolution (i.e., including countries around the world) or city resolution (i.e., including cities around the world). Tools with regional scope are those that include multiple countries in one or more discrete world regions. Tools that were available for individual countries are not reviewed here due to their limited geographical scope. Five national scope tools are summarized in the Supplemental Material and include the Air Quality Benefits Assessment Tool (AQBAT) and the Illness Cost of Air Pollution tool (ICAP) for Canada, the Integrated Transport and Health Impact Modeling Tool (ITHIM) for the United Kingdom, and the Co-Benefits Risk Assessment Screening Model (COBRA) and AP2 (formerly APEEP) model for the United States.

3. KEY TECHNICAL CHARACTERISTICS

Of the 12 tools, nine have global scope, encompassing countries and/or cities around the world (Tables I–III). Four of these tools are designed to be flexible in scope and can be used for

Table I. Key Technical Characteristics of Tools with Global Scope

Characteristic	AirCounts™	AIRQ2.2	BenMAP-CE	EBD	GMAPS	IOMLIFET	LEAP-IBC	SIM-Air	TM5-FASST
Spatial resolution:									
Regional		x	x	x		x		x	x
National		x	x	x	x	x	x		x
City-level	x	x	x	x	x	x		x	
Pollutants:									
Any grid		x	x	x		x			
$PM_{2.5}$	x (primary)	x	x	x		x	x	x[a]	x
PM_{10}		x		x	x	x		x	
Ozone		x	x			x	x		x
NO_2		x	x				x		x
SO_2		x	x						x
CO			x						
Other		Black smoke				*Any affecting mortality*			
Health outcome:									
Mortality (cases)	x	x	x	x	x	x	x	x	x
Disability-adjusted life years (DALY) or years of life lost (YLL)		x	x	x	x	x			x
Morbidity (cases)		x	x	x		x		x	

[a]The SIM-air framework outputs all the criteria pollutants, with linkages for use of all the relevant pollutants in the regional/urban chemical transport models. Only in case of the health impacts, PM is considered as the target pollutant.

analyses ranging from the local to global resolutions (AirQ2.2, BenMAP-CE, EBD, IOMLIFET). The three remaining tools apply to a specific region of the world encompassing several countries (Tables IV–VI). Summary descriptions of the 12 tools are included in the Supplemental Material.

After having provisionally selected a tool based on its predefined geographic scope, the analyst would also consider: how spatially resolved the impact estimates are (region/nation/administrative boundary), which pollutants and health effect outcomes the tool is preconfigured to assess, the method for characterizing population exposure (Sections 3.1 and 3.2), and choice of concentration-response functions and demographic characteristics (Section 3.3). Additional operational factors may also be important: format, accessibility, complexity, and degree of peer review and application in policy contexts (Section 4). The following sections describe each of these key characteristics.

3.1. Pollutants and Health Effect Outcomes

The tools reviewed here differ in terms of pollutants addressed and health outcomes quantified. All tools reviewed in this article except one (GMAPS) are preconfigured to assess fine particulate matter ($PM_{2.5}$) impacts, though AirCounts™ includes only primary $PM_{2.5}$ (excluding secondarily formed sulfate, nitrate, and secondary organic aerosols). Most tools are readily able to estimate coarse particulate matter (PM_{10}) and ozone impacts, and some include NO_x, SO_x, and CO. A few tools also include other pollutants such as heavy metals and black smoke.

Similarly, all the tools reviewed here calculate impacts of air pollution on premature mortality in terms of the number of excess or avoided deaths. However, most tools are set up to quantify "all cause mortality," or deaths from any cause, including those that are associated with air pollution, such as cardiovascular disease, as well as those that are not associated with air pollution, such as accidents and infectious disease. In most cases, particularly for developing countries, it is necessary to extrapolate epidemiologically-derived relative risk estimates from one country to another given the lack of air pollution epidemiology studies in many countries and often greater confidence in estimates of concentration-mortality risk associations based on all available studies as compared to a smaller number of studies in a particular location. In such cases, it may be more appropriate to quantify cause-specific mortality, such as cardiovascular or respiratory mortality, rather than all-cause mortality, as the

Table II. $PM_{2.5}$ Concentration-Response, Population, and Baseline Incidence Data Sources for Tools with Global Scope

Characteristic	AirCounts™	AIRQ2.2	BenMAP-CE	EBD	GMAPS	IOMLIFET	LEAP-IBC	SIM-Air	TM5-FASST
$PM_{2.5}$ concentration-response relationship:									
User-defined		x	x			x	x		
American Cancer Society[3,56]	x	x	x		x	x	x	x	x
GBD Integrated Exposure Response[15]			x	x			In prep		x
Other		x	x						
Population data source:									
User-defined		x	x	x		x			
United Nations	x								x
CIESIN[a]		x			x		x	x	x
Other			x						
Baseline incidence data source:									
User-defined		x		x		x			
World Health Organization	x		x		x			x	x
Other							x	x	

[a]Center for International Earth Science Information Network (CIESIN), available at www.ciesin.org.

Table III. Key Operational Characteristics of Tools with Global Scope

Characteristic	AirCounts™	AIRQ2.2	BenMAP-CE	EBD	GMAPS	IOMLIFET	LEAP-IBC	SIM-Air	TM5-FASST
Format:									
Software download		x	x						
Microsoft office program				x	x	x	x	x	x
Web based	x						In prep		In prep
Open source		x	x	x	x	x	x	x	In prep
Proprietary	x								x
Peer reviewed/policy applications:									
Peer reviewed	In prep	Expert	x	x	In prep	x	In prep	x	In prep
Used for policy applications		x	x		x	x	x	x	x

underlying mix of causes of death can vary greatly between populations. The recently published IER curves connecting $PM_{2.5}$ concentrations to causes of death (ischemic heart disease, cerebrovascular disease, chronic obstructive pulmonary diseases, lung cancer, and acute lower respiratory infections) may now be used for many applications where population-specific risk information is unavailable, as they draw from studies around the world and across a wide range of concentrations.[14,53] These curves have not yet been parameterized in all the tools described here. Many tools can also quantify YLLs, DALYs, and morbidity cases (e.g., respiratory and cardiovascular hospital admissions, cases of chronic obstructive pulmonary disorder). Most tools, such as BenMAP-CE and the LEAP-Integrated Benefits Calculator (LEAP-IBC), estimate impacts attributable to air quality changes in a single year, though these impacts may lag over a multi-year period. The IOMLIFET model can characterize the change in the risk of premature death among a cohort of individuals over the course of their lifetime.[54]

Quantifying air-pollution-related morbidity impacts around the world is made difficult by the

Table IV. Key Technical Characteristics of Tools with Regional (i.e., Multiple Countries in One World Region) Scope

Characteristic	Aphekom	EVA	EcoSense
Region:	Europe	Northern Hemisphere	Europe
National		x	x
City-level	x	x	x
Grid		x	x
Pollutants:			
$PM_{2.5}$	x	x	x
PM_{10}	x	x	x
Ozone	x	x	x
NO_2		x	x
SO_2		x	x
CO		x	
Other		Dioxins, mercury, black carbon	Heavy metals, dioxins, radio nuclides
Health outcome:			
Mortality (cases)	x	x	x
Disability-adjusted life years (DALY) or years of life lost (YLL)	x	x	x
Morbidity (cases)	x	x	x

lack of high-quality baseline morbidity rates in many countries.[22] These types of administrative records are generally more challenging to collect than death records. Therefore, while several of the tools with global scope have the capability to quantify morbidity impacts, the capability may be limited to certain contexts and applications where high-quality baseline morbidity rates are available. In addition, extrapolating concentration-response associations for morbidity outcomes like hospitalizations and asthma attacks from one population to another is difficult because health-care access and systems differ widely around the world and both diagnoses and coding of diagnoses can be inconsistent.

3.2. Resolution and Exposure Characterization

A key difference among the tools reviewed here is their approach to characterizing population exposure to air pollution, changes in exposure resulting from emission or concentration changes, and whether ambient pollutant data are available in the tool or whether users must specify these data from an external source (Table VII). Methods for characterizing exposure often determine the spatial resolution at which air-pollution-related health impacts are calculated and results reported. Some tools assign air quality values to a grid, wherein the geographical scope is divided into cells (either uniform or variable in shape) and population exposure and health impacts are quantified separately for each cell. Other tools assign air quality data to geopolitical boundaries, such as countries, regions of countries, and cities. Ideally, the spatial resolution of the tool and input data would be matched with the spatial resolution of the assessment context (e.g., using a tool with city-level or finer resolution to assess air pollution impacts in cities).

Most tools rely upon air quality modeling to estimate exposure, though some may also be able to read in observations from air quality monitors or draw information from both models and monitors. Compared with monitoring, the advantages of using models to simulate air pollutant concentrations for health impact assessment include broader spatial coverage compared to *in situ* ground-based monitoring (though this may not be the case for satellite-based observations) and the possibility to evaluate different future scenarios of emission changes. By contrast, monitoring data reflect actual ambient levels in a specific location for a discrete period in time. Certain tools (e.g., Aphekom, BenMAP-CE) allow users to adjust these monitoring data to reflect hypothetical air quality changes (i.e., monitor "rollback").

Some of the tools reviewed here can be used to estimate air-pollution-related health impacts at gridded resolution (e.g., BenMAP-CE, EcoSense). Several of these tools use as an input the results of full air quality modeling—which in turn accounts for the complex atmospheric chemistry and transport governing air pollution and also simulates the influence of emission controls on air pollution levels. However, application of these tools may be prohibitive in some assessment contexts because full-scale air quality modeling is generally resource intensive and operating the tool requires significant technical expertise (though web-based and classroom training is often available). The spatial resolution of the available population data may also be a limiting factor for fine-scale analyses. Gridded assessments can typically be aggregated to geopolitical boundaries such as cities (though depending on the grid resolution, there may only be one or two grid cells for each city), countries, and regions.

Table V. $PM_{2.5}$ Concentration-Response, Population, and Baseline Incidence Data Sources for Tools with Regional Scope

Characteristic	Aphekom	EVA	EcoSense
$PM_{2.5}$ concentration-response relationship:			
User-defined		x	
American Cancer Society[56]	x	x	
Other	Several others[57–59]	WHO	WHO[47]
Population data source:			
User-defined	x	x	
Other		GEOSTAT	JRC population density grid[60] with enhancements
Baseline incidence data source:			
User-defined	x		
World Health Organization		x	
Other			EUROSTAT, national statistics

Table VI. Key Operational Characteristics of Tools with Regional Scope

Characteristic	Aphekom	EVA	EcoSense
Format:			
Software download		x	
Microsoft office program	x		
Web based			x
Open source	x		
Proprietary		x	x
Peer reviewed/policy applications:			
Peer reviewed	x	x	x
Used for policy applications	x	x	x

When air quality modeling is unavailable, "reduced-form" tools can generate broad-scale estimates of air pollution impacts. We define here reduced-form tools as those that connect emissions to health impacts using built-in parameterizations, thereby bypassing the need to run expensive and resource-intensive chemical transport modeling. Reduced-form tools often rely on built-in relationships between emissions and the exposure metric (typically concentration) derived from externally conducted air quality model simulations. For example, LEAP-IBC relies on influence coefficients generated by the global chemical transport model, GEOS-Chem Adjoint, that links gridded emissions to impacts at the national level. Another example is the TM5-FASST tool, which is driven by a region-to-region source-receptor matrix (i.e., the quantified influence of emissions in one region on health impacts in another) that was developed from TM5 global chemical transport model simulations. EcoSense uses country-to-grid matrices derived from various EMEP Unified Model runs, i.e., delivers gridded results while using parameterized air pollution modeling. However, the results may be less able to account for atmospheric chemistry and transport than those based on full-form modeling (i.e., taking the difference between separate model simulations of a base case and a control case), as they typically linearize source-receptor relationships that are nonlinear in nature due to nonlinear atmospheric chemistry. Thus, they may be of limited interpretability in certain contexts (e.g., estimating the health benefits of reducing SO_2 emissions after NO_x emission reductions are in place). While reduced-form tools have some limitations, including in their ability to capture complex atmospheric chemistry processes, in many cases these limitations can be reasonable to accept—for example, when screening a large number of emission control scenarios for which air quality modeling would be resource-prohibitive.

Using air quality models for health impact assessment also has several disadvantages, including that simulated concentrations have inherent uncertainty and that the air quality model may not have sufficient resolution to match actual exposure patterns (e.g., near-roadway exposures, high urban concentrations). Similarly, modeled concentrations may not match the method or spatial resolution of the exposure characterization in the epidemiology studies from which concentration-response associations are drawn, which may introduce error into the analysis. Thus, while air quality models are necessary to address health benefits of alternative future scenarios across broad spatial scales, simulated concentrations should be evaluated against observations and care must be taken to match spatial resolutions among the assessment context, air quality model, and epidemiological inputs to the health impact

Table VII. Source Type and Required User Input (Emissions, Concentration, or Intake Fraction) for Population Exposure Information for Each Tool According to the Categories of Geographical Scope

Exposure Information Source	User Input	Global Scope	Regional Scope
Any concentration input by user	Concentration	BenMAP-CE[a] AirQ2.2 IOMLIFET	EBD
In situ monitor	Concentration		Aphekom[b]
Global chemical transport model (input by user)	Concentration		EVA
Regional or urban atmospheric chemistry model (input by user)	Emissions	SIM-Air	EVA
Reduced-form chemical transport model	Emissions	LEAP-IBC[c] TM5-FASST[d]	EcoSense[d]
Reduced-form econometric model	Economic and climate indicators	GMAPS[e]	
Intake fraction (primary $PM_{2.5}$ only)	Emissions	AirCounts™ [f]	

[a]Preloaded with monitor data for the United States and China.
[b]Air quality monitoring data described by Pascal *et al.*[(21)]
[c]Emissions are translated to concentrations and impacts using gridded per unit emission influence coefficients.
[d]Emissions are translated to concentrations and impacts using a nationally averaged source-receptor matrix.
[e]Inputs are: total primary energy consumption by type of energy, per capita gasoline and diesel consumption, country and city population, population density, suite of city-specific climate variables, heating degree days, cooling days, gross national income per capita, gross domestic product, technical progress, historical PM, and total suspended particulate (TSP) concentrations where available.
[f]The intake fractions used in AirCounts™, described by Apte *et al.*,[(61)] are limited to directly emitted $PM_{2.5}$ and cannot be used to estimate secondarily formed pollutants (e.g., ozone, secondarily formed $PM_{2.5}$ components such as sulfate and nitrate).

function as closely as possible. Some tools use *in situ* ground-level monitors, finely resolved population information, or remote sensing (e.g., satellite observations) to improve the performance and resolution of current concentrations simulated by the model (e.g., LEAP-IBC, TM5-FASST). This type of data assimilation, however, is not possible for model simulations of future air quality[(24,55)] or present-day "what if" scenarios, for which observed data are not available. Methods that draw information from both monitors and models can improve confidence in concentration estimates in such cases.

3.3. $PM_{2.5}$ Concentration-Response Relationships, Population, and Baseline Incidence Data Sources

As shown in Tables II and V, a relative commonality among the tools is that many use the same sources of data for concentration-response relationships, population, and baseline incidence rates (e.g., annual number of deaths in a particular population). Several of the global and regional tools are flexible enough to allow users to input data from any source for each of these key inputs to the health impact function.

For $PM_{2.5}$ concentration-response relationships, three of the global tools allow users to input data from any source. At the time of this survey, all but one of the tools with global scope were preconfigured with long-term $PM_{2.5}$ concentration-response relationships based on findings from the American Cancer Society Study.[(3,56)] Three are now using the IERs functions generated for the 2010 GBD Study,[(14,15)] which generate a single concentration-response curve across the entire range of $PM_{2.5}$ concentrations using ambient air pollution, indoor air pollution, and cigarette smoking studies. By contrast, none of the three regional tools use the IERs. Most of the tools do not impose a low-concentration threshold, beyond which health risks per unit pollutant concentration diminish, though many allow a threshold to be specified by the user. Uncertainty in the health impact results may increase at low concentrations (less than approximately 5 $\mu g/m^3$ $PM_{2.5}$ annual average) where epidemiological data are currently sparse. An assumption of linearity at very low concentrations may distort the true health impacts of air pollution in relatively clean atmospheres.[(21,24)] Contrastingly, applying a low-concentration threshold can understate health impacts at low concentrations if the relationship is linear or close to linear. Thus, just as understanding the shape of the concentration-response curve at high concentrations is critical for assessments in highly polluted atmospheres, understanding the shape of the curve at low concentrations may be critical for assessments in relatively clean atmospheres, such as in many economically developed countries. Generally, estimates at such low concentrations impact more on estimates of the burden of current pollution than on estimates of the benefits of pollution reductions (where both old and new concentrations may be above 5 μg/m^3 $PM_{2.5}$ annual average).

For population, four of the tools allow users to input data from any source, five use data from Columbia University's Center for International Earth Science Information Network (CIESIN), and two use U.N. data for each country. Rather than these global data sources, the regional tools use data from any sources or from sources specific to the region. For baseline incidence rates, four of the global tools allow users to input data from any source, five use World Health Organization (WHO) information for regions or countries, and two also use other sources of information. Of the regional tools, one tool allows users to input baseline incidence information from any source, one is preconfigured with WHO data, and one uses other information sources.

4. KEY OPERATIONAL CHARACTERISTICS

The tools also range in format, affecting how accessible they are to less technical audiences. Some tools are client-based software programs, requiring users to download and install the software to use it. These tools include extensive data sets of health impact functions, population, and health data that users may modify, but are generally more complicated to use and may require users to invest time and resources in training themselves. Other tools run within Microsoft Excel, which is generally accessible to most users but may require them to purchase the Microsoft Office suite. Since many analysts are familiar with Microsoft Office, these tools may not require extensive training materials. A few tools are web based, enabling users to generate air pollution health impact estimates without downloading or installing a program. Web-based tools may be most accessible to nontechnical users, particularly in countries that lack the resources to conduct full-scale, detailed, and very refined health impact assessments.

Users may also wish to consider the complexity of the tool (e.g., data inputs and resources required) and the extent to which it is preloaded with the data needed to perform an assessment. The range of tools described here reflects a range of technical complexity and accessibility. Users will want to consider balancing their tolerance for technical complexity with the level of specificity called for in the policy context. For example, the health benefits of U.S. air quality policies are generally estimated using the most refined tool for the U.S. (BenMAP-CE), detailed demographic data sets, and the difference between air quality model simulations of a base emissions scenario and a control emission scenario. In contrast, it may be time and cost prohibitive to run air quality modeling for more data- and resource-limited countries; in the absence of more refined tools and data sets that are also accessible with limited resources, reduced-form tools (e.g., the LEAP-IBC) that do not require air quality modeling or detailed demographic data sets as inputs may be the only way to estimate health benefits of reducing emissions in those areas. It may be useful to work iteratively, using "lighter" tools initially to scope the issues and to see what matters; and moving to more resource-intensive tools only if the scoping indicates that it would be worthwhile to do so. Generally, more refined tools and data inputs allow for greater certainty and precision in results.

Analysts may also consider whether the tool has been peer reviewed, the extent to which analysts have used it to inform policy, and whether it is open source or proprietary. Some tools (e.g., BenMAP, the predecessor to BenMAP-CE) have received external peer review and have been "exercised" extensively in the course of supporting national air quality regulations (e.g., U.S. EPA National Ambient Air Quality Standards). The majority of the tools are either currently open source or open-source versions are in development. A critical advantage of open-source tools over those that are proprietary is that they are fully transparent, allowing analysts to evaluate the underlying algorithms and data sets used to calculate impacts.

Finally, analysts may consider whether the tool is maintained as a "living" tool, or whether the included data sets and methods are fixed in place or obsolescent. The data inputs to air pollution health impact assessments are often updated over time to reflect changes in the science. For example, the size of the population exposed to air pollution is a major driver of air pollution health impacts, and updating data sets over time can capture growth, aging, and migration changes. Similarly, updating baseline mortality and disease rates over time can capture the "epidemiological transition" from infectious disease to chronic disease as economies develop. Air pollution exposure levels are also changing rapidly as economies develop and urbanization occurs, and exposure characterization methods can be updated to reflect the latest emissions, meteorology, and atmospheric chemistry information. On a more operational level, some tools requiring software downloads (e.g., AirQ2.2) may not function on updated operating systems.

5. CHALLENGES

Despite significant advancements in quantifying the health impacts of ambient air pollution over the last decade, several uncertainties and information gaps remain. This section describes key uncertainties that propagate throughout the air pollution health impact assessment methodology (Section 5.1), the degree to which ambient air pollution health impact assessment tools have been integrated with other health risks (Section 5.2), and challenges in interpreting technical information generated by air pollution health impact assessments for use in policy decisions (Section 5.3).

5.1. Uncertainty and Information Gaps

Air pollution health impact assessment combines information from different sources, including estimated pollutant exposure, demographics, and the relationship between ambient concentrations and health outcomes. Each of these information sources carries with it some degree of uncertainty that influences the precision and confidence in the health impact results (Fig. 2). These uncertainties propagate as the health impact assessment moves through each stage, with the relative influence of each parameter's uncertainty dependent on the concentration-response association used to quantify health impacts as well as the assessment context. Characterizing the total uncertainty in the health risk and impact results, and representing it in ways that are both accessible and accurate, is challenging because the magnitude of uncertainty in each of these individual information sources is often unknown and not estimated.

Many air pollution health impact assessments express the quantitative level of uncertainty by calculating a confidence interval using the standard error from the epidemiologically-derived concentration-response relationship. Since the differences between epidemiological effect coefficients are typically larger than the uncertainty of individual effect coefficients,[62] some tools (e.g., BenMAP-CE) allow for simple pooling techniques (e.g., fixed effect and random effects) to combine multiple effect coefficients, leveraging the different populations and study methods of each. However, additional uncertainties exist as to the shape of the concentration-response curve at different concentration levels (i.e., the slope of the concentration-response factor at different concentrations), the extent to which different air pollutant mixtures pose more or less risk, and the degree to which concentration-response relationships found in one population can be extrapolated to others with different lifestyles, age structures, and medical care (e.g., from a U.S. cohort to other countries).

In addition to uncertainties in the concentration-response association, exposure estimates are subject to uncertainties in the magnitude and spatial distribution of emissions, chemical and physical processes influencing the impact of emissions on pollutant concentrations, and the spatial (horizontal) and altitudinal (vertical) resolution. However, uncertainty characteristics of many air quality models are difficult to ascertain. For assessments of future health impacts, uncertainties in socioeconomic assumptions such as economic growth and population health are also important. Although we are more confident in recent estimates of population size and spatial distribution, other demographic parameters, including the baseline mortality and morbidity rates around the world, are uncertain. Projecting future demographic changes is subject to uncertainties regarding population aging, migration, and the epidemiological transition from infectious disease to chronic diseases, which are more affected by air pollution exposure.

Because their magnitude is unknown and not estimated, the uncertainty in each of these parameters is often excluded from the characterization of uncertainty in the health impact assessment results, which may give a misimpression as to the precision and confidence of the results. This is particularly important in assessments for which some unquantified sources may be orders of magnitude more important to the results than the standard error in the concentration-response association. For example, global health impact assessments that incorporate the standard error from the concentration-response association into the confidence intervals around the results exclude a likely much larger source of uncertainty from inaccurate global air pollution emissions and concentrations, as well as the extrapolation of concentration-response associations from one country to the rest of the world.[22–24] The 2010 Global Burden of Disease analysis represented an improvement in characterizing uncertainties from multiple sources as it reported confidence intervals that reflected uncertainty from two input parameters:

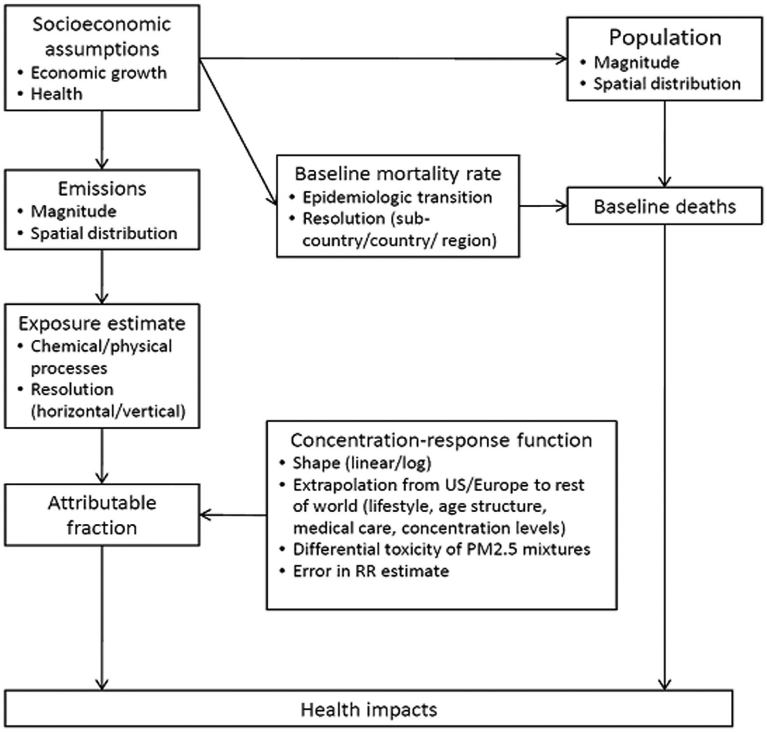

Fig. 2. Sources of uncertainty affecting quantification of air-pollution-related health impacts. RR = relative risk.

(1) the predicted air quality levels and (2) the effect coefficient from the epidemiological study.[15] However, the study did not quantitatively address uncertainty in other parameters, such as population mortality rates. Contrasting global-scale assessments with U.S. assessments where information is rich and air quality monitors extensive, the parameter that has the largest influence on health impact results has been found to be the effect coefficient, followed by the air quality change examined.[62] These two examples of global and U.S. assessments demonstrate that the most influential uncertainty sources likely differ between assessment contexts.

None of the tools surveyed here are capable of fully accounting for all sources of uncertainty, though the limitation lies mainly with the lack of information about input parameter uncertainty as opposed to building into the tools the ability to statistically combine multiple uncertainty sources. In the absence of quantitative uncertainty estimates in each parameter, analysts may consider other methods of addressing error in the input parameters. For example, benchmarking simulated air pollution concentrations against readings from *in situ,* satellite, and other observatory techniques and adjusting the concentration levels used as input to the health impact assessment can help minimize bias introduced by the air quality model.[17] Sensitivity analyses can also provide useful information as to the influence of error in various parameters.[24] Sensitivity analysis is particularly useful for parameters for which observations to compare against do not exist (e.g., projected future demographics). Tools that allow for users to alter individual parameters can be used effectively to conduct sensitivity analyses; those that more rigidly build in data sets that cannot be altered are less able to be used for this purpose. Future assessments that incorporate multiple sources of uncertainty into the results can provide a more complete indication of the uncertainty magnitude. Regardless of the extent to which uncertainties are quantified, it is useful to discuss all uncertainty sources qualitatively with some interpretation by the analyst as to the potential importance of each uncertainty source.

5.2. Integrating Ambient Air Pollution Health Impacts with Other Health Risks

Comparative risk assessments that account for multiple health stressors, such as indoor air pollution, cigarette smoking, climate change, vehicle accidents, and physical activity, can provide greater understanding and context for the impacts of multiple risk factors on society.[15] The tools reviewed here focus on ambient air pollution, but several new tools seek to quantify household air pollution health impacts and capture the interplay between air pollution and other health risks. Several tools under development compile information on household air pollution exposures in different countries (e.g., World Health Organization global database of household air pollution measurements, available at http://www.who.int/indoorair/health_impacts/databases_iap/en/). Other tools are being developed to go beyond household air pollution exposure characterization to health impacts. For example, the Household Air Pollution Impacts Tool (HAPIT, available at https://hapit.shinyapps.io/HAPIT/) developed by University of California–Berkeley allows users to input reductions in indoor air pollution exposure concentrations to estimate premature deaths and DALYs avoided in every country. The tool also includes the ability to compare benefits against mitigation costs to generate estimates of cost effectiveness. Since household emissions can contribute significantly to outdoor air pollution in many places around the world, this type of tool could be integrated with ambient air pollution health impact tools to assess the total benefits of household air pollution mitigation due to exposure both indoors and outdoors, avoiding double counting.

Policies affecting air quality can also influence other sources of risk. For example, encouraging commuters to substitute bicycles in place of automobiles may reduce air pollution and bring health benefits due to physical exercise but increase risk of traffic accidents. To date, only a couple of tools are capable of assessing air pollution health impacts and other population health factors (including cigarette smoking, vehicle accidents, noise, and physical activity) within the same framework. The International Futures project at the University of Denver (http://pardee.du.edu/) integrates household air pollution and ambient air pollution impacts into a much broader global model that includes economic, health, environmental, technological, and other changes over time. The IOMLIFET model can incorporate relative risks for any risk factor, including air pollution and other health risks—provided that the end user can provide the appropriate risk parameters. Finally, the Integrated Transport and Health Impact Modeling Tool (ITHIM) for the United Kingdom integrates health impact assessment of transport through changes in physical activity, road traffic injury risk, and urban air pollution (see Supplemental Material).

Other tools can assess a variety of health risks within the same framework, but have not included the capability to assess air pollution health impacts. The Lives Saved Tool (LiST; http://www.jhsph.edu/departments/international-health/centers-and-institutes/institute-for-international-programs/list/index.html), which allows users to estimate the global health benefits of public health interventions (e.g., vitamin A supplementation and malaria treatments), may soon include the ability to estimate the benefits of household air pollution interventions.[63] The Health Economic Assessment Tool (http://www.heatwalkingcycling.org) includes the impact of increased walking and cycling on health, but does not currently include the capability to quantify air pollution health impacts. Expand the existing tools to quantify air pollution and other health risks in a rigorous and integrated way can provide more complete information to decisionmakers and others.

As air pollution and climate are interrelated in several ways, tools may also increasingly consider both of these health stressors together. In addition to air pollutants that contribute to climate change (e.g., black carbon, ozone) and the influence of climate change on air pollution (e.g., via changing emissions and meteorology), health-harmful air pollutants and long-lived greenhouse gases like CO_2 are often emitted by the same sources. Therefore, some mitigation measures will likely influence both air pollution and climate change simultaneously.[24,26,31] To account for the multiple impacts of changing emissions, the LEAP-IBC quantifies impacts of emission changes on human health, climate change, and agricultural yields simultaneously. Some evidence also suggests that the health effects of air pollutants are modified by temperature, indicating that the health risks imposed by climate change and air pollution may be synergistic.[64,65] Tools that integrate climate change and air pollution impacts therefore provide a more comprehensive accounting of impacts that can be informative for policy decisions.[55]

5.3. Interpreting Technical Information for Policy Decisions

Another challenge not fully accounted for in these tools is interpreting and reporting the results such that they are well matched to the objective of the risk assessment. The types of results provided and how they are explained may differ for different assessment contexts. For example, for assessments intended to provide information about the burden

Table VIII. Example Assessment Contexts, Key Technical and Operational Considerations When Selecting an Air Pollution Health Impact Assessment Tool, and Potentially Appropriate Tools to Use for the Assessment

Assessment Context	Key Considerations	Potentially Appropriate Tools
National ambient air quality standards regulatory support in data-rich country	Maximize technical rigor. Resources are typically available for air quality modeling or measurements. Standards are concentration based rather than emissions based.	AirQ2.2 Aphekom (Europe) BenMAP-CE EBD (Europe) EVA (Northern Hemisphere) IOMLIFET National-scale tools not included in this survey
National ambient air quality standards regulatory support in data-poor country	Resources for air quality modeling or measurements are typically not available. Reduced-form tools can provide an order of magnitude assessment. Standards are concentration based rather than emissions based.	AirQ2.2 Aphekom (Europe) BenMAP-CE global module
Hypothetical reduction of $PM_{2.5}$ concentrations to WHO guidelines	This hypothetical scenario does not require information about the magnitude of emission reductions. The tool may input concentrations rather than emissions. Reduced-form tools can provide an order of magnitude assessment.	AirQ2.2 Aphekom (Europe) BenMAP-CE global module (global) EVA
Reduced air pollution emissions resulting from multi-governmental agreements (e.g., on climate change, long-range transboundary air pollution)	Resources may be available for global chemical transport modeling, but reduced-form tools can provide an order of magnitude assessment. Analysis starts with emissions rather than concentrations.	AirQ2.2 BenMAP-CE IOMLIFET LEAP-IBC TM5-FASST GMAPS EVA
Reduced air pollution emissions from international development projects (e.g., World Bank, Global Environment Facility)	Project developers typically responsible for providing information about the benefits of the project in their application are unlikely to have air quality modeling expertise. Reduced-form tools can provide an order of magnitude assessment. Spatial resolution must most closely match the scale of the project (typically urban).	AirCounts^{TM} (primary $PM_{2.5}$ in urban areas) Aphekom (Europe) BenMAP-CE global module LEAP-IBC EcoSense (Europe) SIM-Air EVA

of disease due to air pollution exposure for non-regulatory purposes, it may be sufficient to provide only a limited set of quantitative estimates, including cases of death and disease.[15,17] Conversely, assessments intended to inform the setting and design of regulations may require more extensive analyses and results, including the percentage reduction in the air pollution health burden, various sensitivity analyses, uncertainty estimation, and all assumptions underlying these results.[45] Risk analysts can more effectively communicate if they thoroughly understand the data sets, calculations, and assumptions used to produce risk results, as well as which values and analyses to highlight.[66] Policymakers can make more informed decisions if they have an appreciation of what information is and *is not* represented by the values provided to them.

The tools surveyed here produce results in a variety of formats, including different types of numerical results, descriptions, charts, graphs, and maps. They range in the extent of explanations given for each result type, and the extent to which they rely on the analyst to understand the parameters, equations, and results on their own. The challenge is perhaps greatest with reduced-form tools that have built-in parameters that the user cannot change; these parameters are typically produced using an external model during the development of the tool and users of these tools may not be aware of or understand how they were produced. While easily applied tools are more accessible, if not fully understood by the end user, they may enable misuse or misinterpretation of findings, potentially leading to poorly designed policies. Overly automated tools thus have the potential to undermine the ability of analysts to fully understand their own assessments. Tools that are flexible enough to allow users to input their own data sets, tools that are open source, and tools that are extensively documented and peer reviewed can ease this challenge significantly. In the future, guidance could assist users in interpreting numeric results from air pollution health impact assessment tools and communicating results to decisionmakers. Where possible, these tools could be used in the context of training of environmental health professionals to be able to share the philosophy behind the tool, and this type of guidance could be incorporated into training materials for individual tools with specific application to the type of results (e.g., avoided mortality cases, life expectancy changes, percent reduction in air pollution mortality burden) produced by the tool.

6. CONCLUSION

This article reviews 12 current and publicly available multinational tools that combine air quality information, epidemiologically-derived concentration-response associations, and demographic data sets to estimate air-pollution-related health risks. Nine of the tools are capable of assessing air pollution health risks in cities, countries, and/or regions around the world or on a gridded resolution at any geographical scope from local to global (we define these to be global in scope). Three of the tools encompass several countries (we define these to be regional in scope). The tools share several common attributes. Nearly all estimate $PM_{2.5}$ impacts (though two include only the directly emitted components of $PM_{2.5}$), consider mortality outcomes, and are open source. Many of the tools also use similar data sources for concentration-response associations, population, and baseline mortality rates. The tools also vary in important respects, including the exposure information sources, format, and technical complexity.

Different tools are appropriate for different assessment contexts, and analysts must consider the technical and operational specifications of the tool necessary to meet the needs of the assessment context. The range of key characteristics among the tools demonstrates that there is an important tradeoff between technical refinement and accessibility for a broad range of applications. For some purposes, it may be sufficient to use a coarsely resolved global tool based on reduced-form air quality modeling given data and resource and time limitations. Even in geographical areas for which high-quality data exist, reduced-form tools may be useful to screen many potential emission scenarios, identifying those that may benefit from more detailed evaluation. However, where possible, more finely resolved and sophisticated tools based on full air quality modeling allow for greater confidence and precision in results, particularly useful for regulatory analysis. And when sufficient air pollution measurements, provided by air quality monitoring networks, are available, they also provide a reliable source of a population's exposure.[20] Given the heterogeneity among technical and operational characteristics, analysts may wish to select tools that provide the appropriate geographic scope, resolution, and maximum degree of technical rigor within the resource (e.g., data, time, technical capability) constraints.

Matching the abilities of individual tools with specific assessment contexts could highlight ways in which the currently available tools could be improved or whether new methods or tools are needed to fill a specific need. To demonstrate the technical and operational considerations when selecting a tool to perform the assessment, Table VIII provides an initial matching of potentially appropriate tools to example assessment contexts. This table does not represent the variety of assessment contexts that these tools are often asked to inform, nor does it reflect consensus among the tool developers as to how their tools are most appropriately used. Nevertheless, it demonstrates how specific tools can be matched to different assessment contexts. A systematic intercomparison among the inputs, assumptions, calculations, and results of the various health risk assessment tools surveyed here would help analysts identify the tool most appropriate for different assessment contexts.

In addition to a systematic tool intercomparison, there are opportunities to better account for multiple sources of uncertainty and to integrate health risks from multiple stressors, including ambient outdoor air, indoor air pollution, cigarette smoking, climate change, vehicle accidents, and physical activity. Such integrated risk assessments can provide greater understanding and context for the impacts of multiple risk factors on society. In addition, increasing the extent to which these tools and their underlying data, formulas, and documentation are publicly available and open source can enhance transparency, reproducibility, and the ability for outside investigators to make improvements.

ACKNOWLEDGMENTS

The authors alone are responsible for the views expressed in this publication and they do not necessarily represent the decisions or stated policies of their employers. This article was expanded from a white paper prepared while S. Anenberg was employed by the U.S. Environmental Protection Agency. We thank Ed Hanna, Daven Henze, Denise Mulholland, Nicholas Muller, Dave Stieb, Marko Tainio, Harry Vallack, and Jason West for useful contributions. We appreciate helpful comments received during the WHO Expert Meeting on Health Risk Assessment and Convention on Long-Range Transboundary Air Pollution Task Force on Health meetings in Bonn, Germany, May 12–14, 2014.

REFERENCES

1. Bell ML, McDermott A, Zeger SL, Samet JM, Dominici F. Ozone and short-term mortality in 95 US urban communities, 1987–2000. JAMA, 2004;292(19):2372–2378.
2. Jerrett M, Burnett RT, Pope CA III, Ito K, Thurston G, Krewski D, Shi Y, Calle E, Thun M. Long-term ozone exposure and mortality. New England Journal of Medicine, 2009; 360:1085–1095.
3. Krewski D, Jerrett M, Burnett RT, Ma R, Hughes E, Shi Y, Turner MC, Pope CA III, Thurston G, Calle EE, Thun MJ, Beckerman B, DeLuca P, Finkelstein N, Ito K, Moore DK, Newbold KB, Ramsay T, Ross Z, Shin H, Tempalsi B. Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality. Boston: Health Effects Institute, 2009.
4. Lepeule J, Laden F, Dockery D, Schwartz J. Chronic exposure to fine particles and mortality: An extended follow-up of the Harvard Six Cities Study from 1974 to 2009. Environmental Health Perspectives, 2012; 120(7):965–970.
5. World Health Organization. Air Quality Guidelines. Global Update 2005. Copenhagen, Demark: World Health Organization, 2006.
6. U.S. Environmental Protection Agency (U.S. EPA). Integrated Science Assessment (ISA) for Sulfur Oxides — Health Criteria (Final Report). EPA/600/R-08/047F. Washington, DC: U.S. Environmental Protection Agency, 2008.
7. U.S. Environmental Protection Agency (U.S. EPA). Integrated Science Assessment for Particulate Matter (Final Report). EPA/600/R-08/139F. Washington, DC: U.S. Environmental Protection Agency, 2009.
8. U.S. Environmental Protection Agency (U.S. EPA). Integrated Science Assessment of Ozone and Related Photochemical Oxidants (Final Report). EPA/600/R-10/076F. Washington, DC: U.S. Environmental Protection Agency, 2013.
9. U.S. Environmental Protection Agency (U.S. EPA). Integrated Science Assessment for Oxides of Nitrogen (Health Criteria) — Second External Review Draft. EPA/600/R-14/006. Washington, DC: U.S. Environmental Protection Agency, 2015.
10. Health Effects Institute (HEI). Special Report 17: Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure and Health Effects. Boston, MA: Health Effects Institute, 2010.
11. Laumbauch RJ, Kipen HM. Respiratory health effects of air pollution: Update on biomass smoke and traffic pollution. Journal of Allergy Clinical Immunology, 2012; 129(1): 3–11.
12. Delfino RJ, Wu J, Tjoa T, Gullesserian S, Nickerson B, Gillen DL. Asthma morbidity and ambient air pollution: Effect modification by residential traffic-related air pollution. Epidemiology, 2014; 25(1):48–57.
13. Wesson K, Fann N, Morris M, Fox T, Hubbell B. A multi-pollutant risk-based approach to air quality management: Case study for Detroit. Atmospheric Pollution Research, 2010; 1:296–304.
14. Fann N, Wesson K, Hubbell B. Characterizing the confluence of air pollution risks in the United States. Air Quality Atmosphere, and Health, 2015; doi: 1007/s11869-015-0340-9.
15. Burnett RT, Pope CA, Ezzati M, Olives C, Lim SS, Mehta S, Shin HH, Singh G, Hubbell B, Brauer M, Anderson HR, Smith KR, Balmes JR, Bruce NG, Kan H, Laden F, Pruss-Ustun A, Turner MC, Gapstur SM, Diver WR, Cohen A. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. Environmental Health Perspective, 2014; 122(4):397–403.
16. Lim SS, Vos T, Flaxman AD, Danaei G, Shibuya K, Adair-Rohani H, et al. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: A systematic analysis for the Global Burden of Disease Study 2010. Lancet, 2013; 380(9859):2224–2260.
17. Hubbell BJ, Hallberg A, McCubbin D, Post E. Health-related benefits of attaining the 8-hr ozone standard. Environmental Health Perspective, 2005; 113(1):73–82.
18. Fann N, Lamson AD, Anenberg SC, Wesson K, Risley D, Hubbell BJ. Estimating the national public health burden associated with PM2.5 and ozone. Risk Analysis. 2011; 32(1):81–95.
19. Anderson HR, Ruggles R, Pandey KD, Kapetanakis V, Brunekreef B, Lai CK, Strachan DP, Weiland SK. Ambient particulate pollution and the world-wide prevalence of asthma, rhinoconjunctivitis and eczema in children: Phase one of the International Study of Asthma and Allergies in Childhood (ISAAC). Occupational and Environmental Medicine, 2009; 67(5):293–300.
20. Henschel S, Atkinson R, Zeka A, Le Tertre A, Analitis A, Katsouyanni K, Chanel O, Pascal M, Forsberg B, Medina S, Goodman PG. Air pollution interventions and their impact on public health. International Journal of Public Health, 2012; 57(5):757–768.
21. Pascal M, Corso M, Chanel O, Declercq C, Badaloni C, Cesaroni G, Henschel S, Meister K, Haluza D, Martin-Olmedo P, Medina S. Assessing the public health impacts of urban air pollution in 25 European cities: Results of the Aphekom project. Science of Total Environment, 2013; 449:390–400.
22. Cohen AJ, Anderson HR, Ostro B, Pandey KD, Krzyzanowski M, Kunzli N, Gutschmidt K, Pope CA III, Romieu I, Samet JM, Smith KR. Urban air pollution. Pp. 1353–1434 in Ezzati M, Lopez AD, Rodgers A, Murray CJL (eds). Comparative Quantification of Health Risks: Global and Regional Burden of Disease Due to Selected Major Risk Factors. Geneva: World Health Organization, 2004.
23. Anenberg SC, Horowitz LW, Tong DQ, West JJ. An estimate of the global burden of anthropogenic ozone and fine particulate matter on premature human mortality using atmo-

spheric modeling. Environmental Health Perspectives, 2010; 118(9):1189–1195.
24. Anenberg SC, Talgo K, Arunachalam S, Dolwick P, Jang C, West JJ. Impacts of global, regional, and sectoral black carbon emission reductions on surface air quality and human mortality. Atmospheric Chemistry and Physics, 2011; 11:7253–7267.
25. Anenberg SC, Schwartz J, Shindell D, Amann M, Faluvegi G, Klimont Z, Janssens-Maenhout G, Pozzoli L, Van Dingenen R, Vignati E, Emberson L, Muller NZ, West JJ, Williams M, Demkine V, Hicks WK, Kuylenstierna J, Raes F, Ramanathan V. Global air quality and health co-benefits of mitigating near-term climate change through methane and black carbon emission controls. Environmental Health Perspectives, 2012; 120(6):831–839.
26. Shindell D, Faluvegi G, Walsh M, Anenberg SC, Van Dingenen R, Muller NZ, Austin J, Koch D, Milly G. Climate, health, agricultural, and economic impacts of tighter vehicle-emission standards. Nature Climate Change, 2011; 1:59–66.
27. West JJ, Smith SJ, Silva RA, Naik V, Zhang Y, Adelman Z, Fry MM, Anenberg S, Horowitz LW, Lamarque J-F. Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health. Nature Climate Change, 2013; 3:885–889.
28. Chambliss SE, Silva R, West JJ, Zeinali M, Minjares R. Estimating source-attributable health impacts of ambient fine particulate matter exposure: Global premature mortality from surface transportation emissions in 2005. Environmental Research Letters, 2014; 9:104009.
29. Anenberg SC, West JJ, Fiore AM, Jaffe DA, Prather MJ, Bergmann D, Cuvelier K, Dentener FJ, Duncan BN, Gauss M, Hess P, Jonson JE, Lupu A, MacKenzie IA, Marmer E, Park RJ, Sanderson MG, Schultz M, Shindell DT, Szopa S, Vivanco MG, Wild O, Zeng G. Intercontinental impacts of ozone pollution on human mortality. Environmental Science & Technology, 2009; 43:6482–6487.
30. Anenberg SC, West JJ, Yu H, Chin M, Schulz M, Bergmann D, Bey I, Bian H, Diehl T, Fiore A, Hess P, Marmer E, Montanaro V, Park R, Shindell D, Takemura T, Dentener F. Impacts of intercontinental transport of anthropogenic fine particulate matter on human mortality. Air Quality, Atmosphere and Health, 2014; 7(3):369–379.
31. Brandt J, Silver JD, Christensen JH, Andersen MS, Bønløkke J, Sigsgaard T, Geels C, Gross A, Hansen AB, Hansen KM, Hedegaard GB, Kaas E, Frohn LM. Assessment of past, present and future health-cost externalities of air pollution in Europe and the contribution from international ship traffic using the EVA model system. Atmospheric Chemistry and Physics. 2013b; 13:7747–7764.
32. Likhvar VN, Pascal M, Markakis K, Colette A, Hauglaustaine D. A multi-scale health impact assessment of air pollution over the 21st century. Science of the Total Environment, 2015; 514:439–449.
33. He K, Lei Y, Pan X, Zhang Y, Zhang Q, Chen D. Co-benefits from energy policies in China. Energy, 2010; 35(11):4265–4272.
34. Boldo E, Linares C, Lumbreras J, Borge R, Narros A, Garcia-Perez J, Fernandez-Navarro P, Perez-Gomez B, Aragones N, Ramis R, Pollan M, Moreno T, Karanasiou A, Lopez-Abente G. Health impact assessment of a reduction in ambient PM2.5 levels in Spain. Environment International, 2011; 37(2):342–348.
35. Boldo E, Linares C, Aragones N, Lumbreras J, Borge R, de la Paz D, Perez-Gomez B, Fernandez-Navarro P, Garcia-Perez J, Pollan M, Ramis R, Moreno T, Karanasiou A, Lopez-Abente G. Air quality modeling and mortality impact of fine particulate matter reduction policies in Spain. Environmental Research, 2014; 128:15–26.
36. Fann N, Nolte CG, Dolwick P, Spero TL, Curry Brown A, Phillips S, Anenberg S. The geographic distribution and economic value of climate change-related ozone health impacts in the United States in 2030. Journal of the Air & Waste Management Association, 2015; 65(5):570–580.
37. Nawadha A. Reductions of PM2.5 air concentrations and possible effects on premature mortality in Japan. Water, Air, & Soil Pollution, 2013; 224:1508.
38. Guttikunda SK, Jawahar P. Application of SIM-air modeling tools to assess air quality in Indian cities. Atmospheric Environment, 2012; 62:551–561.
39. Brandt J, Silver JD, Christensen JH, Andersen MS, Bønløkke J, Sigsgaard T, Geels C, Gross A, Hansen AB, Hansen KM, Hedegaard GB, Kaas E, Frohn LM. Contribution from the ten major emission sectors in Europe to the health-cost externalities of air pollution using the EVA model system — An integrated modelling approach. Atmospheric Chemistry and Physics, 2013; 13:7725–7746.
40. Guttikunda SK, Goel R. Health impacts of particulate pollution in a megacity — Delhi, India. Environmental Development, 2013; 6:8–20.
41. Guttikunda SK, Khaliquzzaman M. Health benefits of adapting cleaner brick manufacturing technologies in Dhaka, Bangladesh. Air Quality Atmosphere and Health, 2014; 7(1):103–112.
42. Guttikunda SK, Lodoysamba S, Bulgansaikhan B, Dashdondog B. Particulate pollution in Ulaanbaatar, Mongolia. Air Quality Atmosphere and Health, 2013; 6(3):589–601.
43. Kheirbeck I, Wheeler K, Walters S, Kass D, Matte T. PM2.5 and ozone health impacts and disparities in New York City: Sensitivity to spatial and temporal resolution. Air Quality Atmosphere and Health, 2013; 6(2):473–486.
44. Holland M, Hunt A, Hurley F, Navrud S, Watkiss P. Service contract for carrying out cost-benefit analysis of air quality related issues, in particular in the Clean Air for Europe (CAFE) Programme. Methodology for the cost-benefit analysis for CAFE: Volume 1: Overview of methodology. Web published: AEA Technology Environment, 2005. Available at: http://europa.eu.int/comm/environment/air/cafe/activities/cba.htm.
45. Amann M (ed). Policy scenarios for the revision of the Thematic Strategy on Air Pollution. TSAP Report #10. Laxenburg, Austria: International Institute for Applied Systems Analysis, March 2013.
46. U.S. Environmental Protection Agency (U.S. EPA). Regulatory Impact Analysis for the Final Revisions to the National Ambient Air Quality Standards for Particulate Matter. EPA-452/R-12-005. Washington, DC: U.S. Environmental Protection Agency, 2012.
47. World Health Organization. Health Risks of Air Pollution in Europe — HRAPIE Project. Recommendations for Concentration–Response Functions for Cost–Benefit Analysis of Particulate Matter, Ozone and Nitrogen Dioxide. Copenhagen, Denmark: World Health Organization, 2013.
48. Le Tertre A, Schwartz J, Touloumi G. Empirical Bayes and adjusted estimates approach to estimating the relation of mortality to exposure of PM. Risk Analysis, 2005; 25(3):711–718.
49. Fiore A, Dentener FJ, Wild O, Cuvelier C, Schultz MG, et al. Multimodel estimates of intercontinental source-receptor relationships for ozone pollution. Journal of Geophysical Research, 2009; 114:D04301.
50. Rao ST, Galmarini S, Puckett K. Air quality model evaluation international initiative (AQMEII). Bulletin of the American Meteorological Society, 2011;92:23–30.
51. Lamarque J-F, Shindell DT, Josse B, Young PJ, Cionni I, Eyring V, Bergmann D, Cameron-Smith P, Collins WJ, Doherty R, Dalsoren S, Faluvegi G, Folberth G, Ghan SJ, Horowitz LW, Lee YH, MacKenzie IA, Nagashima T, Naik

V, Plummer D, Righi M, Rumbold S, Schulz M, Skeie RB, Stevenson DS, Strode S, Sudo K, Szopa S, Voulgarakis A, Zeng G. The Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP): Overview and description of models, simulations and climate diagnostics. Geoscientific Model Development, 2013; 6:179–206.
52. World Health Organization. WHO Expert Meeting: Methods and Tools for Assessing the Health Risks of Air Pollution at Local, National, and International Level. Meeting Report. Copenhagen, Denmark: World Health Organization, 2014.
53. Pope CA III, Cropper M, Coggins J, Cohen A. Health benefits of air pollution abatement policy: Role of the shape of the concentration-response functions. Journal of the Air & Waste Management Association, 2015; 65(5):516–522.
54. Miller BG, Hurley JF. Life table methods for quantitative impact assessments in chronic mortality. Journal of Epidemiology & Community Health, 2003; 57:200–206.
55. Geels C, Andersson C, Hänninen O, Lansø AS, Schwarze P, Brandt J. Future premature mortality due to air pollution in Europe — Sensitivity to changes in climate, anthropogenic emissions, population and building stock. International Journal of Environmental Research and Public Health, 2015; 12:2837–2869.
56. Pope CA, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, Thurston GD. Lung cancer, cardiopulmonary mortality and long-term exposure to fine particulate air pollution. JAMA, 2002; 287:1132–1141.
57. Anderson HR, Atkinson WA, Peacock JL, Marston L, Konstantinou K. Meta-Analysis of Time-Series Studies and Panel Studies of Particulate Matter (PM) and Ozone (O3). Report of a WHO Task Group. Copenhagen: World Health Organization, 2004.
58. Atkinson RW, Anderson HR, Sunyer J, Ayres J, Baccini M, Vonk JM, Boumghar A, Forastiere F, Forsberg B, Touloumi G, Schwartz J, Katsouyanni K. Acute effects of particulate air pollution on respiratory admissions. American Journal of Respiratory and Critical Care Medicine, 2005; 164(10):1860–1866.
59. Gryparis A, Forsberg B, Katsouyanni K, Analitis A, Touloumi G, Schwartz J, Samoli E, Medina S, Anderson HR, Niciu EM, Wichmann HE, Kriz B, Kosnik M, Skorkovski J, Vonk JM, Dortbudak Z. Acute effects of ozone on mortality from the "Air pollution and health a European approach" Project. American Journal of Respiratory Critical Care Medicine, 2004; 170(10):1080–1087.
60. Gallego FJ. A population density grid of the European Union. Population and Environment, 2010; 31:460–473.
61. Apte J, Emilie B, Julian M, William N. Global intraurban intake fractions for primary air pollutants from vehicles and other distributed sources. Environmental Science & Technology, 2012; 46(6):3415–3423.
62. Mansfield C, Sinha P, Henrion M. Influence analysis in support of characterizing uncertainty in human health benefits analysis, Final Report. 2009; U.S. Environmental Protection Agency. Available at: http://www.epa.gov/ttn/ecas/regdata/Benefits/influence_analysis_final_report_psg.pdf, Accessed April 17, 2015.
63. Bruce NG, Dherani MK, Das JK, Balakrishnan K, Adair-Rohani H, Bhutta ZA, Pope D. Control of household air pollution for child survival: Estimates for intervention impacts. BMC Public Health, 2013; 13(Suppl 3):S8.
64. Ren C, Williams G, Mengersen K. Temperature enhanced effects of ozone on cardiovascular mortality in 95 large US communities, 1987–2000: Assessment using the NMMAPS data. Archives of Environmental & Occupational Health, 2009; 64(3):177–184.
65. Jhun I, Fann N, Zanobetti A, Hubbell B. Effect modification of ozone-related mortality by temperature in 97 US cities. Environment International, 214; 73:128–134.
66. Medina S, Le Tertre A, Saklad M. On behalf of the Apheis collaborative network. The Apheis project: Air pollution and health — A European information system. Air Quality Atmosphere and Health, 2009; 2(4):185–198.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's website:

Online Supplement

Table S1. Key Technical Characteristics of Tools with National Scope

Table S2. Key Operational Characteristics of Tools with National Scope