Estimating the Health and Economic Impacts of Changes in Local Air Quality

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Objectives. To demonstrate the benefits-mapping software Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE), which integrates local air quality data with previously published concentration–response and health–economic valuation functions to estimate the health effects of changes in air pollution levels and their economic consequences.

Methods. We illustrate a local health impact assessment of ozone changes in the 10-county nonattainment area of the Dallas–Fort Worth region of Texas, estimating the short-term effects on mortality predicted by 2 scenarios for 3 years (2008, 2011, and 2013): an incremental rollback of the daily 8-hour maximum ozone levels of all area monitors by 10 parts per billion and a rollback-to-a-standard ambient level of 65 parts per billion at only monitors above that level.

Results. Estimates of preventable premature deaths attributable to ozone air pollution obtained by the incremental rollback method varied little by year, whereas those obtained by the rollback-to-a-standard method varied by year and were sensitive to the choice of ordinality and the use of preloaded or imported data.

Conclusions. BenMAP-CE allows local and regional public health analysts to generate timely, evidence-based estimates of the health impacts and economic consequences of potential policy options in their communities. (*Am J Public Health.* 2018;108:S151–S157. doi:10.2105/AJPH.2017.304252)

Potential changes in the National Ambient Air Quality Standards or local proposals to eliminate sources of air pollution frequently generate local and regional discussions about the implications of these changes on the affected communities and industries. Central to these discussions are the effects of poor air quality on human health and agriculture, the potential economic consequences of pollutant exposure or pollutant mitigation, and the community's preparedness to address potential changes. Quantitative assessments of the health and economic impacts of changes in national standards and local mitigation plans can inform air quality management strategies intended to benefit human health by reducing pollution levels.[1]

Frequently, environmental scientists, engineers, and public health practitioners are called on to participate in such discussions by performing environmental impact assessments, developing local air quality simulation models, and offering informed expert opinions about potential policy changes. Expert contributions in local and regional settings can be bolstered significantly by timely, quantitative estimates of the potential health effects and health-related economic impacts of different air quality standards on the local scale.[2] However, local health impact analyses pose unique methodological challenges,[3] and these analyses have historically required expensive computing resources and technical expertise that are not routinely available to community-based health agencies or local advisory groups.

A variety of sources in the Dallas–Fort Worth (DFW) region emit pollutants that are precursors to ground-level ozone and have thus inhibited the ability of this region to attain the ozone standard. Included among these sources are a number of coal-fired power plants.[4] To explore the benefits from simulated attainment with a hypothetical alternate ozone standard, we undertook a computer modeling project to estimate the magnitude of ozone-attributable health benefits expected to result from improving ozone air quality. We used a new open-source software program called the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE). This tool integrates local air quality data with epidemiological, demographic, and economic data to quantify the health effects and associated economic values of poor air quality.

Earlier versions of BenMAP (version 4.0 and earlier) were applied primarily by technical analysts and academic groups to inform discussions of air quality policy.[5–8] Recently, the Environmental Protection Agency (EPA) released a community edition of BenMAP (available at https://www.epa.gov/benmap), making the software more practical for use by the public health community, local researchers and clinicians, and nongovernmental organizations in the United States and internationally. Other researchers have also begun to employ BenMAP-CE.[9–11]

We present a strategic overview of the BenMAP-CE modeling process, which we illustrate with 2 simulated scenarios in which DFW ozone-monitoring data were reduced or rolled back using a specified algorithm

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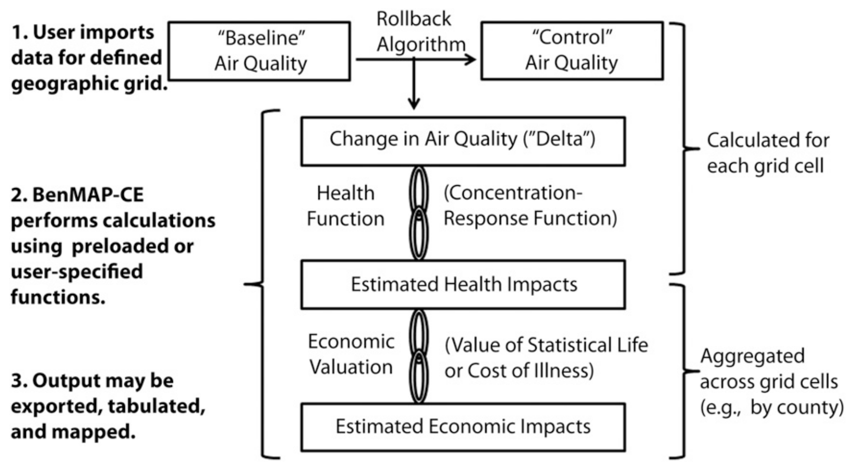
(a rollback scenario applied in the software): (1) an incremental rollback of 10 parts per billion applied to the daily 8-hour maximum (D8HourMax) ozone metric at all area ozone monitors, and (2) a rollback of D8HourMax ozone values to a hypothetical alternate standard applied to the subset of local monitors that measure ozone levels above such a hypothetical alternate standard. We describe several important considerations for future users and offer recommendations about the application and publication of BenMAP-CE results. These methods may be applied to other geographic settings, pollutant metrics, or air quality scenarios, allowing generation of a variety of timely, region-specific, evidence-based estimates of the health effects and economic consequences of potential policy options. We offer more detailed explanations for future BenMAP-CE users in Appendix A (available as a supplement to the online version of this article at http://www.ajph.org).



Note. BenMAP-CE = Environmental Benefits Mapping and Analysis Program-Community Edition. BenMAP-CE software calculates a change in air quality between 2 air quality scenarios and estimates the health and economic impacts of this change. We imported a baseline air quality data set from the area under study (the Dallas–Ft. Worth 10-county nonattainment region) from the Environmental Protection Agency Web site, and the software defined a control air quality data set by a user-specified rollback algorithm. The software performs calculations for each cell in a geographic grid and aggregates the results to a geographic scale of interest (e.g., county or region level).

FIGURE 1—Overview of BenMAP-CE Software

METHODS

BenMAP software, developed by a team of programmers located in the United States and China,[12] applies air quality scenarios over a defined geographic extent and pollutant season and integrates this information with quantitative estimates of the health impacts of selected pollutant exposures, using pollutant concentration–response functions from the published literature or as otherwise specified by the user. BenMAP then estimates the economic impacts of these health effects using evidence-based valuation techniques, which are effectively economic weighting schemes.

Figure 1 provides an overview of the steps in a BenMAP-CE analysis, which are described in more detail in Appendix A. We used BenMAP-CE version 1.1. We performed additional data management and mapping procedures with SAS version 9.4 (SAS Institute, Inc., Cary, NC) and ArcMap version 10.2 (Environmental Systems Research Institute, Redlands, CA).[13]

Grid Definition

We used ArcMap 10.2 to create a DFW area grid consisting of 1-kilometer square grid cells. The grid extended throughout the DFW study area, which is composed of the 10 counties Dallas, Tarrant, Denton, Wise, Collin, Parker, Rockwall, Johnson, Ellis, and Kaufman, which comprise a nonattainment area for the 2008 EPA ozone standard.[4] Using ArcMap, we projected the grid to the geographic coordinate system (North American Datum 1983) specified by BenMAP-CE technical documentation.[14]

Pollutant Metrics

BenMAP-CE contains preloaded pollutant definitions for ground-level ozone and particulate matter measuring less than 2.5 microns in diameter, applying metrics used to quantify each day's air quality at each monitoring station for the EPA's National Ambient Air Quality Standards.[15] We used the D8HourMax metric in this study. The D8HourMax metric for a certain monitor is constructed by selecting the highest of all the running 8-hour averages of each day's hourly ozone readings.[14]

Values of pollutant metrics (e.g., D8HourMax) may be generated in BenMAP-CE for selected years for which the software contains preloaded ozone monitor values (2000–2008 for BenMAP-CE version 1.1). Alternatively, daily ozone levels expressed in these metrics are publicly available for all monitoring stations in the United States[16] and may be downloaded and imported into BenMAP-CE for analysis. We compared results obtained with preloaded and imported data.

Air Quality Data

Our analysis focused on air quality monitoring data for 3 years: 2008, 2011, and 2013. Local and state authorities took major ozone abatement measures in North Texas after 2008,[4] and 2013 had unusually wet, cool summer weather.[17] Because they were not preloaded in BenMAP-CE, we downloaded the daily values of the D8HMax metric from DFW area monitors for 2011 and 2013 from the EPA's AirData Web site[18] and aggregated, processed, and formatted them to BenMAP-CE import specifications[14,19] using SAS 9.4. To compare results from preloaded data and imported data, we also downloaded, processed, and imported monitor data according to these specifications for 2008.

To avoid edge effects arising from sparse data at the edges of the study area, we incorporated monitor data from all US monitors for both the preloaded and downloaded data sets. We interpolated discrete air quality monitoring values for the D8HourMax metric to create a continuous surface across the 1-kilometer geospatial grid representing the 10-county DFW area. We applied the Voronoi Neighborhood Averaging interpolation method, selecting the default parameter in BenMAP-CE that did not constrain the interpolation to a specific distance from each monitor.

Changes in Air Quality

BenMAP-CE estimates the health impact of a potential policy option or environmental mitigation effort by calculating the changes (deltas) in a population's cumulative exposure over the pollutant season from a set of prechange air quality measurements (baseline data set) to a set of postchange values expected from application of the hypothetical set of control measures (which the software refers to as the "control data set").

For our analysis, we calculated discrete deltas using prechange air quality metrics over the ozone season (May–September) for each monitor in the baseline data set (derived from daily air quality data) and postchange values in the control data set (calculated using 2 rollback scenarios) and then interpolated over the 1-kilometer geographic grid (Figure 1; Appendix B [available as a supplement to the online version of this article at http://www.ajph.org]).

Air Pollution Rollback Scenarios

BenMAP-CE offers 3 predefined rollback strategies: percentage rollback, incremental rollback, and rollback-to-a-standard (Appendix A)[14]; we compared the last 2. The incremental rollback algorithm allows the user to reduce the anthropogenic portion of each daily ozone metric from the baseline data set by a user-specified increment (e.g., 10 ppb) before placing it in the control data set. It makes this adjustment to the daily metrics from all monitors in the geographic area of interest. By contrast, the rollback-to-a-standard algorithm allows the user to stipulate a hypothetical air quality standard, expressed as a new level of an ozone metric that should not be exceeded on any day during the year (e.g., the D8HourMax ozone metric should not exceed 65 ppb, a level being discussed in the DFW scenario).

The software applies an attainment test to the daily values of that air quality metric over the year in the baseline data set to determine whether all the daily values are at or below the stipulated hypothetical alternate standard (i.e., the monitor was "in attainment"—or meeting the hypothetical alternate standard—for the year) and rolls back to the level of the standard the values for monitors that fail the attainment test.[14]

To approximate a data-smoothing feature of the EPA's national standards,[15] the rollback-to-a-standard algorithm applies an ordinality parameter and trims the highest value or values before applying the attainment test. For example, the highest of the daily values of the D8HourMax metric over the year is called the "first ordinality" (no high values trimmed); the second highest is the "second ordinality" (the single highest value trimmed); and so on for the third and fourth highest values (the third and fourth ordinalities, respectively). Our analysis compared the first and fourth ordinalities. (For more details, see Appendix A.)

BenMAP-CE rollback strategies distinguish between the nonanthropogenic background level and the anthropogenic level (i.e., ozone above the background level). Rollbacks are applied only to levels above the nonanthropogenic background. We specified a nonanthropogenic background ozone concentration of 40 parts per billion,[6,7] a value consistent with policy-relevant background ozone levels in the DFW area.[20]

Health Impact Functions

BenMAP-CE contains a number of preloaded concentration–response health impact functions derived from the literature. These are estimated parameters from publications of large epidemiologic studies and meta-analyses that describe the associations of changes in pollutant concentrations with changes in health outcomes, including short-term mortality or disease-specific endpoints such as asthma-related emergency department visits or hospital admissions. Users may import additional health impact functions.

We compared 4 short-term mortality health impact functions associated with the D8HourMax ozone metric to demonstrate the operation of BenMAP-CE software. "Short-term mortality" refers to deaths within days after an air quality measurement and is often expressed in air quality statistical models with a 1- to 4-day lag term. The first 2 health impact functions, which are among those preloaded in BenMAP, associate ozone levels with all-cause, short-term mortality: the Bell et al.[21] and Levy et al.[22] health impact functions for D8HourMax.[14] For comparison, the other 2 associate ozone levels with nonaccidental, short-term mortality: Schwartz,[23] also a function preloaded in BenMAP-CE,[14] and Madrigano et al.,[24] a function that we derived from the literature (as shown in Appendix A) and loaded into BenMAP-CE.

The specified parameter estimates and SDs for the 4 health impact functions used in this analysis are summarized in Table 1. Corresponding to the original studies in which each health impact function was developed, these apply to short-term mortality among all age groups during the ozone season.

Estimation of Health Impacts

BenMAP-CE estimates the health effects for each cell in the defined geographic grid with the following equation:

TABLE 1—Parameter Estimates From 4 Health Impact Functions Estimating the Association of the D8HourMax Ozone Metric With Short-Term Mortality During the Ozone Season (May–September)

Source of the Health Impact Function	Mortality Endpoint	Estimate (SD)
Bell et al.[21]	All cause, short term	0.000795 (0.000212)
Levy et al.[22]	All cause, short term	0.001121 (0.000180)
Madrigano et al.[24]	Nonaccidental, short term	0.000548 (0.000155)
Schwartz[23]	Nonaccidental, short term	0.000426 (0.000150)

Note. D8HourMax = daily 8-hour maximum. All 4 parameter estimates have a normal distribution. Those described by Bell et al., Levy et al., and Schwartz came preloaded in BenMAP-CE; we imported that of Madrigano et al. into the software. Parameters of health impact functions are referred to as "betas" in the software user interface and documentation.

$$\text{(1) Avoidable Premature Deaths} = [1-(1/e^{\beta\times\delta})] \times \textit{Incidence} \times \textit{Population} \times A,$$

where β is defined by the health impact function, δ corresponds to the estimated air quality change per grid cell over the course of the pollutant season, and A is a scalar constant (0.0027397) converting annual mortality rates to daily mortality rates.

County-level mortality or disease incidence rates and population denominator data can be drawn from preloaded BenMAP-CE data or user-provided data sets. We used preloaded 2010 county-level baseline mortality rates and 2010 US Census population data covering the DFW 10-county population of approximately 6.3 million people.

Economic Valuation

BenMAP-CE estimates the economic value of each estimated health impact by applying evidence-based valuation functions, such as the "value of a statistical life" for mortality endpoints. These valuation options, their projected values over time, and their distributions are described in the software's technical documentation.[14]

We generated economic estimates with a preloaded BenMAP-CE valuation function—the Weibull-distributed value of a statistical life estimate—derived from a set of 26 valuation functions from the economics literature and commonly used for regulatory impact analyses.[14] This method assigns a value of approximately $8 million (in 2010 dollars in our study) to each death attributable to a specified air quality problem. The method we used applies economic valuation functions that do not vary by age. However, our analysis does account for differences in the baseline rate of death across populations of different ages, which serves as a proxy for susceptibility to air pollution–related risk of death. Users may specify alternative economic valuation methods in BenMAP-CE, including those that account for differences in age or quality of life.

Aggregation and Pooling of Results

Estimated health effects and economic valuations may be aggregated across cells of the geographic grid to provide more interpretable estimates, such as county-level or regional impacts. Health impacts calculated from different health impact functions can also be pooled, when appropriate. For our DFW area analyses, we aggregated results to the county level (Appendix B).

Processing Results

Air quality changes (deltas), health effects, and economic valuations can be exported from BenMAP-CE in comma-separated values files, which may be directly interpreted or further processed using other software packages. Users may export nonaggregated results (e.g., preventable mortality for each cell in the 1-km grid for the DFW area) as well as aggregated results (e.g., preventable mortality for each county). For our study, BenMAP-CE output was aggregated and analyzed in SAS version 9.4.

RESULTS

The BenMAP-CE analyses estimated the numbers of deaths and their economic value at the county level in 2008, 2011, and 2013 that would have been prevented by specified reductions in daily ozone levels and how the estimates vary by the choice of rollback scenarios: incremental rollback and rollback-to-a-standard.

Incremental Rollback

Table 2 shows the number of avoided premature deaths expected to result from a 10–parts per billion incremental rollback of the baseline ozone levels, comparing results obtained using 4 different health impact functions for short-term mortality (listed in Table 1). Each analysis yields the sum of avoidable deaths across the 10-county DFW area and the associated economic value, which is estimated with the value of a statistical life valuation function.

As anticipated, estimates calculated by the 2 all-cause mortality functions were similar, whereas estimates calculated by the 2 nonaccidental mortality functions were lower than were those calculated by the all-cause mortality functions. Estimates using the incremental rollback method were relatively insensitive to the source of the data (i.e., preloaded vs imported data) and the year of analysis (i.e., similar across the 3 years when the same health impact function was applied).

Rollback-to-a-Standard

Table 2 shows the number of avoidable deaths expected to result from a rollback of all baseline ozone levels exceeding a hypothetical alternate ozone standard of 65 parts per billion to that level. All rollback-to-a-standard estimates, obtained using the Bell et al.[21] health impact function for all-cause short-term mortality (listed in Table 1), compare the effects of 2 ordinality choices. By contrast to the relatively stable estimates obtained by the incremental rollback method, results from the rollback-to-a-standard method showed greater year-to-year variability and were sensitive to both the choice of ordinality and the use of preloaded or imported data.

County-Level Estimates

Figure A in Appendix B shows the cumulative ozone exposure over the ozone season (deltas) estimated from the 2008 preloaded daily ozone values from each EPA air quality monitor (locations shown in the figure) with our BenMAP-CE model, using the Bell et al.[21] health impact function for a 10–parts per billion incremental rollback and interpolated between the monitors over the 1-kilometer square grid cells (grid lines not shown) across the 10-county DFW nonattainment area (county boundary lines shown). The pattern of the exposure levels results from the formation of ozone from nitrogen oxides and volatile organic compounds emitted primarily from coal-fired power plants, cement kilns, and motor vehicle exhaust drifting northwest on the prevailing southeasterly warm season winds. The distribution of county-specific preventable premature deaths avoided by the 10–parts per billion rollback (shown in parentheses in the figure) reflect differences in the 10 counties' population sizes and cumulative ozone exposure levels.

DISCUSSION

A common purpose of air quality management planning is to improve human health. The EPA's new open-source software

TABLE 2—Avoidable Premature Deaths and Associated Economic Valuations Estimated by 2 BenMAP-CE Rollback Methods for the D8HourMax Ozone Metric: Dallas–Fort Worth Region, TX, May–September of 2008, 2011, and 2013

Source of the Health Impact Function	Type of Short-Term Mortality Outcome	Ordinality	2008[a] Deaths	2008[a] Value, $[b] (Millions)	2011[a] Deaths	2011[a] Value, $[b] (Millions)	2013[a] Deaths	2013[a] Value, $[b] (Millions)
By the incremental rollback method calculated from preloaded metrics data[c]								
Bell et al.[21]	All cause	NA	62	493	...	...	...	...
Levy et al.[22]	All cause	NA	87	695	...	...	...	...
Madrigano et al.[24]	Nonaccidental	NA	39	313	...	...	...	...
Schwartz[23]	Nonaccidental	NA	29	229	...	...	...	...
By the incremental rollback method calculated from imported metrics data[c]								
Bell et al.[21]	All cause	NA	64	515	83	662	71	569
Levy et al.[22]	All cause	NA	91	725	116	932	100	801
Madrigano et al.[24]	Nonaccidental	NA	41	327	52	420	45	361
Schwartz[23]	Nonaccidental	NA	30	239	38	308	33	264
By the rollback-to-a-standard method calculated from preloaded metrics data[c,d]								
Bell et al.[21]	All cause	1	86	689	...	...	...	...
Bell et al.[21]	All cause	4	63	503	...	...	...	...
By the rollback-to-a-standard method calculated from imported metrics data[c,d,e]								
Bell et al.[21]	All cause	1	5	40	67	535	51	408
Bell et al.[21]	All cause	4	0	0	11	46	0	0

Note. BenMAP-CE = Environmental Benefits Mapping and Analysis Program-Community Edition; D8HourMax = daily 8-hour maximum; NA = not applicable. Ellipses indicate preloaded data not available for 2011 and 2013. We performed calculations using air quality data for the ozone season, 2010 US Census population denominator data, and 4 short-term health impact functions, against a nonanthropogenic background of 40 ppb.

[a]Local and state authorities took ozone abatement measures after 2008[4]; 2013 had lower ozone levels because of unusually wet, cool summer weather.[18]

[b]Discounted to 2010 dollars.

[c]The incremental rollback algorithm reduces the daily ozone metrics from all monitors by the specified amount (10 ppb in this study), whereas the rollback-to-a-standard algorithm only reduces the increment of the daily metrics that exceeds the chosen standard threshold for monitors not meeting the potential alternate standard (65 ppb in this study). Neither method reduces the metric below the specified nonanthropogenic background level (40 ppb in this study).

[d]Application of the rollback-to-a-standard method to preloaded data appears to generate higher estimates for attributable deaths compared with application of this method to imported data. This appears to result from the presence of hourly data in the preloaded data set compared with D8HMax data in the imported data set.

[e]Estimates from applying the rollback-to-a-standard method to imported data vary greatly from year to year for reasons such as variation in weather, the number of air monitors meeting the potential alternate standard, and metric ordinality.

BenMAP-CE provides an additional tool for public health groups at the local, state, and national level to quantify the health effects of potential policy options. This software combines local air quality measurements with evidence-based computing algorithms to estimate the number of adverse health events that are potentially avoided by environmental policies on the local or regional level—such as hospital admissions, emergency department visits, asthma or chronic lung disease exacerbations, school absences, and deaths—and to calculate the associated economic value.

As we have demonstrated, BenMAP-CE analysis may begin with a local area's air pollution metrics, which can be downloaded from publicly available monitoring data. A rollback algorithm may then be specified in the software to simulate a potential reduction in pollution. Users should be aware that the rollback methods available in BenMAP-CE differ in important ways.

Rollback Methods

The choice of which rollback method to select should be determined by the nature of the problem being addressed. Different abatement strategies affect pollution problems differently, and pollution abatements may affect peak pollution levels differently from lower levels.[25] The incremental rollback method might be preferred for abatements that affect pollution levels throughout the anthropogenic range, whereas the rollback-to-a-standard method might be more appropriate for those that primarily address peak levels. Because peak levels vary over time, the results of the rollback-to-a-standard method are more sensitive to the standard's ordinality and more variable over years because of changes in such conditions as weather.

We identified an inconsistency in this version of the software between analyses run on the preloaded and imported air pollution data (Table 2). When applied to preloaded data sets, the rollback-to-a-standard method appears to calculate the D8HMax metrics from hourly data contained in the data set, generating higher values than those obtained from imported D8HMax metric data. (This is likely related to the presence of higher values for each ordinality among the hourly values compared with the 8-hour, D8HMax, values.) Users may choose to import data sets of their desired metrics (e.g., D8HMax) for rollback-to-a-standard analyses to address this inconsistency.

In addition, because publicly available data sets are subject to verification and correction over time (e.g., identification of erroneous values), directly importing these data at the time of use may ensure that users analyze the most up-to-date version of the monitoring data.

Health Impact Functions

Another important decision for users is the choice of concentration–response health impact functions that translate the change in air pollution metrics into estimated avoidable health outcomes. BenMAP-CE provides health impact functions for a variety of air pollutants and the actual US Census population denominators and background outcome rates for any region of the country. Moreover, the user can import customized health impact functions derived from local studies. Users may select or import the health impact function they decide is most appropriate for the particular air pollutants, population characteristics, and health outcomes of the community under study.

As in our study, health impact functions may not have been defined specifically for the geographic area under study. Some of the most useful health impact functions are derived from studies of a large number of cities such as the National Morbidity, Mortality, and Air Pollution Study, a time-series study of 95 US cities.[22] The scientific articles describing these studies generally provide the locations and pollution levels of each of the participating cities, which might be useful in selecting the most appropriate health impact function.

Economic Valuation Functions

The economic valuation functions for avoidable deaths, as applied in our study, deserve special attention because these estimates are typically large compared with those for other adverse health effects. In general, the value of a statistical life approach combines estimates from many studies in the economics literature, estimating people's willingness to pay to avoid risks by (1) contingent valuation estimated by people in large surveys, and (2) wage–risk studies using wage compensation differentials demanded in the labor market for riskier jobs.[26] The mean of the studies estimates the value of a statistical life, and their distribution influences the variance of the final valuation.

Stipulation of Background

Finally, BenMAP-CE allows stipulation of a nonanthropogenic background ozone level, set at 40 parts per billion in our study,[20] below which the rollback algorithms are not applied. This prevents inflation of benefit estimates from applying health impact functions developed at higher ozone levels to low ozone levels, where the shape of the concentration–response curve might differ.[27] In the future, as ozone levels fall closer to the nonanthropogenic background, the specified upper bound of the nonanthropogenic background level may be lowered. Future analyses may be able to use health impact functions developed to measure the impacts of ozone at levels below 40 parts per billion.[28]

Public Health Implications

BenMAP-CE is a potentially useful tool for informing local or regional discussions about air quality. As our analyses demonstrate, results may be strongly influenced by analytic specifications. Users should carefully consider each step—including grid selection; pollutant and metric definitions; baseline and control scenario specifications (including rollback algorithms and background thresholds); concentration–response functions; and aggregation, pooling, and valuation methods—and determine which analytic methods best match their study question. All analytic steps should be clearly outlined in publications reporting estimates from BenMAP-CE to permit constructive appraisal of the results as well as comparative analyses by other BenMAP-CE users. AJPH

CONTRIBUTORS

M. L. Carvour wrote the first draft of the article and designed and carried out the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) analyses with technical advice from R. W. Haley and N. Fann. A. E. Hughes performed the geographical mapping analyses with ArcMap, preprocessing of air quality data, and postprocessing of BenMAP-CE output. R. W. Haley originated the study. N. Fann provided technical insights into how BenMAP-CE functions. All authors interpreted the data and revised the article.

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HUMAN PARTICIPANT PROTECTION

The University of Texas Southwestern Medical Center's institutional review board determined that the study was not human participants research.

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