ANALYSIS OF $PM_{2.5}$ USING THE ENVIRONMENTAL BENEFITS MAPPING AND ANALYSIS PROGRAM (BENMAP)

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ABSTRACT

As epidemiological work from around the world continues to tie $PM_{2.5}$ to serious adverse health effects, including premature mortality. The U.S. Environmental Protection Agency (U.S. EPA) has developed a number of policies to reduce air pollution, including $PM_{2.5}$. To assist in the benefit-cost analyses of these air pollution control policies, the U.S. EPA has developed the Environmental Benefits Mapping and Analysis Program (BenMAP). BenMAP is meant to 1) provide a flexible tool for systematically analyzing impacts of changes in environmental quality in a timely fashion, 2) ensure that stakeholders can understand the assumptions underlying the analysis, and 3) adequately address uncertainty and variability. BenMAP uses a "damage-function" approach to estimate the health benefits of a change in air quality. The major components of the damage-function approach are population estimates, population exposure, adverse health effects, and economic costs. To demonstrate BenMAP's ability to analyze $PM_{2.5}$ pollution control policy scenarios, we assess 2 sample applications: 1) benefits of a national-level air quality control program, and 2) benefits of attaining 2 annual $PM_{2.5}$ standards in California (annual average standards of 15 $\mu g/m^3$ and 12 $\mu g/m^3$). In the former, we estimate a scenario where control of $PM_{2.5}$ emissions result in \$100 billion of benefits annually. In the analysis of alternative standards, we estimate that attaining the more stringent standard (12 $\mu g/m^3$) would result in approximately 2000 fewer premature deaths each year than the 15 $\mu g/m^3$ achieves. BenMAP has a number of features to help clarify the analysis process. It allows the user to record in a configuration all of the choices made during an analysis. Configurations are especially useful for recreating already existing policy analyses. Also, BenMAP has a number of reporting options, including a set of mapping tools that allows users to visually inspect their inputs and results.

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Disclaimer: The opinions expressed in this article are the authors' and do not necessarily represent those of the United States Environmental Protection Agency.

INTRODUCTION

A wide range of analyses have demonstrated that air pollution is related to many problems, including adverse health effects, agricultural crop losses, visibility reductions, and damage to buildings. In recent years, the health problems associated with particulate matter less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$) have received increasing attention, as epidemiological work from around the world has tied $PM_{2.5}$ to serious adverse health effects, including premature mortality, chronic bronchitis, and hospital admissions. Impact assessments in a variety of settings have consistently identified $PM_{2.5}$ as a major cause of premature mortality and morbidity around the world (e.g., Kunzli et al., 2000). To reduce air pollution, including $PM_{2.5}$, in the United States, the U.S. Environmental Protection Agency (U.S. EPA) has developed a number of approaches, including tighter emission standards on motor vehicles and at industrial sources, reduced sulfur content in diesel fuels, an emissions cap and trading program for sulfur dioxide, and a recent proposal to expand trading to include nitrogen oxides.

Benefit-cost analysis has become an important tool in analyzing air policies. The U.S. Office of Management and Budget (OMB, 2003) recently released a report finding that the benefits of clean-air regulations during the past decade outweighed the costs to industry by at least a factor of five. As air quality standards become more stringent, however, the costs of achieving incremental improvements rise, making it more desirable to weigh the benefits and costs of new policies. Currently, the process of analyzing benefits and costs has a number of weaknesses. One is the time that it takes between proposing a new policy and analyzing its benefits and costs. Another is the black box nature of the analysis, and the difficulty for those outside the analysis process to understand the assumptions underlying it. Yet another is the inherent uncertainty and variability in the approaches used in an analysis. In response, the U.S. EPA is developing the Environmental <u>Ben</u>efits <u>M</u>apping and <u>A</u>nalysis <u>P</u>rogram (BenMAP). The goals are 1) to provide a flexible tool for systematically analyzing the impacts of changes in environmental quality in a timely fashion, 2) to make sure that stakeholders can understand the assumptions underlying the analysis, and 3) to adequately address uncertainty and variability.

A new Windows-based program developed jointly by the U.S. EPA and Abt Associates Inc., BenMAP allows users to estimate the benefits associated with changes in environmental quality. Ambient air quality surfaces can be created from monitored air quality, modeled air quality, or a combination of the two.[3] Potentially exposed populations can be calculated for any year after 1990, using 1990 and 2000 census data along with county-level projections out to 2025 (and simple linear interpolation thereafter). Populations can be further broken down by race, gender, and age. Additionally, BenMAP includes large databases of concentration-response functions and economic valuations of health impacts, and allows users to add new functions and valuations.

BenMAP also allows users to save the details of a particular analysis so that it can be replicated using alternative environmental quality scenarios. This allows users to analyze multiple policies in a systematic fashion, ensuring that the results of each analysis can be compared directly with each other. This ability to create a consistent framework for multiple analyses means that the assumptions underlying the analyses can remain the same over time, making the benefits estimation process more transparent. Additionally, BenMAP stores each decision that a user makes at every step of the analysis so that an audit trail can be generated from all BenMAP output files. This provides a further degree of transparency to analyses.

Finally, BenMAP characterizes uncertainty arising from two sources: the health impact coefficient from the epidemiological study (usually represented by the standard error from the epidemiological study), and the dollar value assigned to each health effect. For each health endpoint, BenMAP generates distributions of incidence estimates, represented by percentiles, and then uses Monte Carlo techniques to sample from the distributions of incidence and unit values to derive distributions of economic values for each health endpoint. The distribution of total economic benefits can then be estimated by Monte Carlo sampling from each of the individual distributions of

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[3] BenMAP can use output from a variety of models including: Regulatory Model System for Aerosols and Deposition (REMSAD), the Comprehensive Air Quality Model with Extensions (CAMx), the Urban Airshed Monitoring - Variable grid model (UAM-V), and the Community Multi-Scale Air Quality model (CMAQ). The following links provide more information on each model: REMSAD: http://remsad.saintl.com/; CAMx: http://www.camx.com; UAM-V: http://uamv.saintl.com/; and CMAQ: http://www.epa.gov/asmdnerl/models3/cmaq.html.

economic values across endpoints. It should be noted that the uncertainty BenMAP quantifies provides insight into how uncertain incidence and valuation estimates are with regard to uncertainty associated with statistical error and cross-study variability. However, BenMAP at this time is unable to provide a probabilistic, multiple-source uncertainty analysis. Key sources of uncertainty not captured by BenMAP include those associated with emissions estimates, air quality modeling, population projections, and aspects of health science and economic valuation not captured in the studies.

This paper first presents the basic framework for calculating the benefits of policy-related changes in air quality. We limit the discussion to estimating and valuing the health impacts directly linked to ambient levels of $PM_{2.5}$, although BenMAP is also able to estimate and value the health effects associated with other pollutants. We then present the results of two sample analyses. In the first case, we estimate the health-related economic benefits of the attainment of a national-level emissions control program. We then present the health-related economic benefits of California meeting the national annual standard for $PM_{2.5}$, and the incremental benefits of California meeting its own lower annual $PM_{2.5}$ standard.

METHODS

BenMAP uses a “damage-function” approach to estimate the health benefits associated with a change in air quality. This approach estimates changes in individual health endpoints, assigns values to these changes, and sums the values for all non-overlapping health endpoints to generate total benefits. It imposes no overall preference structure, and does not account for potential income or substitution effects, so that adding a new endpoint will not reduce the value of changes in other endpoints (Smith et al., 2002). This is the standard approach for most cost-benefit analyses of regulations affecting environmental quality, and it has been used in several recent published analyses (Ostro and Chestnut, 1998; Kunzli et al., 2000; Levy et al., 2001).

Figure 1 illustrates the major steps in the damage function approach: population estimate, population exposure, adverse health effects, and economic costs. BenMAP is built on block-level population data from the 1990 and 2000 U.S. Census and county-level population forecasts out to the year 2025. BenMAP maps the population data to air quality surfaces, which may be generated using either monitor-based air quality data, model-based air quality data, or a combination of the two.

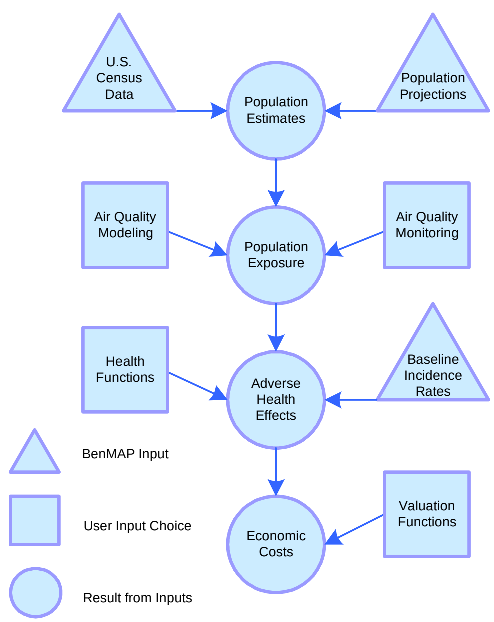

Figure 1. BenMAP policy analysis approach.

Typically, a user will create both a baseline population exposure surface, reflecting current or future-current air quality conditions, and a control surface, reflecting air quality conditions after the implementation of a policy scenario or a rollback of air quality conditions to a particular level, such as the attainment of a standard. The baseline and control population exposure surfaces yield changes in population exposure to ambient air pollution that are then input to health impact functions to generate changes in incidence of health effects. The resulting effects changes are then assigned monetary values. Finally, values for individual health effects are summed to obtain an estimate of the total monetary value of the changes in emissions.

Population

BenMAP population data is built from Census block data containing over two hundred race, gender, and age specific variables. This block level data is aggregated to the various grid definitions used in BenMAP analyses, including uniform grids such as that used by the REMSAD air quality model, and political boundary grids such as United States counties. BenMAP also includes population projections developed by Woods & Poole at the United States county level for each of these race, gender, and age specific variables. BenMAP uses these projections to estimate populations for the years 2001 to 2025 by using the county level ratios of the desired population projection and the year 2000 population. For years beyond 2025, BenMAP uses a simple linear extrapolation of the estimated 2024-2025 trend.

For United States county population data, estimating populations for 2001 and beyond is straightforward. Each race, gender, and age specific variable is scaled by the appropriate population projection ratio in each county. For grid definitions other than United States counties, BenMAP calculates a population-weighted average of the county level population projection ratios for each grid cell. That is, a grid cell might overlap two or more counties. In these cases, BenMAP uses the percentage of the total population in that grid cell which comes from each county to determine a population weighted average of the various county level population projections.[4]

Population Exposure

BenMAP provides multiple ways to estimate exposure, using a combination of air quality monitoring and air quality modeling data. Currently, it does not include emissions data or the ability to do air quality modeling, and instead has a database of air quality monitoring data and the ability to incorporate modeling data from several different air quality models. BenMAP has four broad approaches to estimating exposure: model direct, monitor direct, monitor and model relative, and monitor rollbacks. The air quality exposure estimates are referred to as air quality grids.

BenMAP creates air quality grids to estimate the average exposure to ambient air pollution of people living in some specified area, or domain, such as that delineated by REMSAD, CAMx, UAM-V and CMAQ models, as well as more irregular shapes, such as counties. It is assumed that all persons in a given grid-cell are exposed to the same pollution levels. When using modeling data directly, BenMAP simply converts the input modeling data into an air quality grid file that matches the structure of the model. These model specifications are presented in Table 1. However, when using monitor data, alone or in combination with modeling data, the user may select from two interpolation methods to move from point-based monitor data to the grid-cell-based exposure estimates: Closest Monitor and Voronoi Neighbor Averaging (VNA).

The Closest Monitor method simply assigns the monitor closest to a grid cell's center as its representative value. VNA first identifies the set of monitors that "surround" each grid cell's center (these monitors are referred to as the grid cell's neighbors), and then calculates an inverse-distance weighted average of these neighboring monitors. For each of the interpolation approaches, users specify parameters such as the maximum distance within which to include a monitor, with monitors beyond the specified maximum excluded from the analysis.

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[4] The appendices in the BenMAP user’s manual describe the population data, forecasting approach, and other aspects of the model in detail. The manual is available at http://www.epa.gov/ttn/ecas/models/modeldoc.pdf.

Table 1: Air quality model data structure.

Model	Pollutant [a]	Modeling Domain and Data File Description
REMSAD	$PM_{2.5}$, PM_{10}, and PM Coarse	Two REMSAD Modeling Domains REMSAD12: has grid cells that are 1/6 of a degree longitude wide and 1/9 of a degree latitude high, or about 12 kilometers by 12 kilometers. The modeling domain extends from longitude -126E to -66E and latitude 24E to 52E, with a total of 90,720 grid cells that completely cover the continental United States. REMSAD36: has grid cells that are 1/2 of a degree longitude wide and 1/3 of a degree latitude high, or about 36 kilometers by 36 kilometers. The modeling domain extends from longitude -126E to -66E and latitude 24E to 52E, with a total of 10,080 grid cells that completely cover the continental U.S.
CAMx and UAM-V	Ozone	Modeling Domain CAMx and UAM-V have grid cells that are 1/6 of a degree longitude wide and 1/9 of a degree latitude high, or about 12 kilometers by 12 kilometers. BenMAP assumes a boundary extending from longitude -127E to -67E and latitude 26E to 52E, with a total number of 84,280 grid cells that cover most of the continental United States, with the exception of the southern tips of Florida and Texas.
CMAQ	$PM_{2.5}$, PM_{10}, and PMC	Modeling Domain The modeling domain for CMAQ covers the entire continental United States. The size of each grid cell is roughly comparable to that of REMSAD36.

[a] Note that the different Grid types are limited to specific pollutants. Currently, BenMAP can only input REMSAD and CMAQ model data for particulate matter, and CAMx and UAM-V are limited to ozone.

Users may also conduct monitor rollback analyses, for one or more non-overlapping rollback regions. A region is simply a set of states with an associated set of rollback parameter values. Three rollback types are available - Percentage Rollback, Incremental Rollback, and Rollback to a Standard. Each of these rollback types has different rollback parameters associated with it.

Percentage Rollback. Percentage rollback involves setting only two parameters - a percentage and a background pollution level. The rollback procedure is similarly straightforward - each observation at each monitor in the region has the portion of its value which is above the background pollution level reduced by a percentage.

Incremental Rollback. Incremental Rollback similarly involves setting only two parameters - an increment and a background level. The rollback procedure is similar to the percentage rollback procedure - each observation at each monitor in the region has the portion of its value which is above background level reduced by an increment. The reduced values are not allowed to become negative, however - that is, they are truncated at zero.

Rollback to a Standard. Rollback to a Standard has two groups of parameters - those associated with the Attainment Test, which determines whether a monitor is in attainment (meets the standard), and those associated with the Rollback Methods, which are used to bring out of attainment monitors into attainment.

The Attainment Test parameters are Metric, Ordinality, and Standard. A monitor is considered in attainment if the n^{th} highest value of the metric is at or below the value specified by the standard, where n is the ordinal value. For example, if the $PM_{2.5}$ metric is twenty four hour average, the ordinality is four, and the standard is sixty five $\mu g/m^3$, a monitor will be considered in attainment if the fourth highest twenty four hour average is at or below sixty five $\mu g/m^3$. Ordinality does not apply for the annual average metric, since there is only a single metric value to work with.

For $PM_{2.5}$, the Rollback Method parameters are simply a Rollback Method and a Background Level. There are four supported rollback methods for $PM_{2.5}$ Rollbacks - Percentage, Incremental, Peak Shaving, and Quadratic. For each of these rollback methods, the following definitions are important:

Anthropogenic Out of Attainment Value: The out of attainment value is the metric value that caused the monitor to be considered out of attainment (the fourth highest value, in the above example). The anthropogenic out of attainment value is the portion of the out of attainment value left over after the background level has been subtracted from it.
Anthropogenic Standard: The portion of the Attainment Test Standard left over after the background level has been subtracted from it.

Anthropogenic Metric Values: The portion of each metric value left over after the background level has been subtracted from it (or zero, if the metric value is below the background level).

Non-Anthropogenic Metric Values: For each metric value, either the background level (if the metric value is higher than the background level), or the metric value (if the metric value is less than the background level).

Percentage. To generate rolled back metric values using Percentage rollback, BenMAP calculates the percentage required to reduce the anthropogenic out of attainment value to exactly the anthropogenic standard. This percentage reduction is then applied to all of the anthropogenic metric values. Finally, these reduced anthropogenic metric values are added to the non-anthropogenic metric values to give the final rolled back metric values.
Incremental. To generate rolled back metric values using Incremental rollback, BenMAP calculates the increment required to reduce the anthropogenic out of attainment value to exactly the anthropogenic standard. This incremental reduction is then applied to all of the anthropogenic metric values (but - they are not allowed to fall below zero). Finally, these reduced anthropogenic metric values are added to the non-anthropogenic metric values to give the final rolled back metric values.
Peak Shaving. To generate rolled back metric values using Peak Shaving rollback, BenMAP simply truncates all anthropogenic metric values at the anthropogenic standard. These reduced anthropogenic metric values are added to the non-anthropogenic metric values to give the final rolled back metric values.
Quadratic Rollback. The Quadratic rollback reduces large values proportionally more than small values while just achieving the standard - that is, the anthropogenic out of attainment value should be more or less at the anthropogenic standard after the rollback (though some small amount of error is involved).

Combining Monitoring and Modeling Data

When BenMAP interpolates air quality data using the Monitor and Model Relative option, monitor values are scaled using modeled air quality data. The concept of scaling is to use the modeling data to adjust the interpolated monitor data, and thus combine the advantages of both types of data - the real-world accuracy of the monitoring data and the omnipresence and ability to predict future trends of the modeling data. There are three scaling approaches: Spatial, Temporal, and Spatial and Temporal (combined).[5]

Spatial scaling. Spatial scaling involves an air quality modeling file that matches the same year as the monitoring data. BenMAP scales the concentrations of each neighboring monitor by the ratio of the modeled concentration at the grid cell to the modeled concentration at the grid cell containing the monitor. This approach takes into account what the air quality modeling reveals about spatial heterogeneity in pollution levels. For example, if the monitors are in relatively polluted urban areas, and the grid cell is in a relatively unpolluted rural area, then the scaling will result in multiplying the monitor values with ratios less than one, and thus produce lower values at the rural grid cell than would be estimated with interpolation of the unscaled monitor data.

Spatial scaling is useful because, while monitors provide invaluable information about historical conditions, there are only a limited number of monitors. Many areas, particularly rural areas in the U.S., are not close to monitors. Model data can provide additional information that improves the interpolated concentration estimates, and provides a more accurate picture of air quality.

Temporal scaling. Temporal scaling involves both a base year air and a future year air quality modeling file, and scales the concentrations of each neighboring monitor by the ratio of the modeled concentration at the grid cell

[5] Each scaling approach is documented in detail in Appendix C of the BenMAP user's manual, available at http://www.epa.gov/ttn/ecas/models/modeldoc.pdf.

containing the monitor in the future year to the modeled concentration at the grid cell containing the monitor in the base year. This approach takes into account what the air quality modeling reveals about the changes in pollution levels over time at the monitor sites. For example, if the modeling forecasts that in the future, pollution levels will decrease, then the scaling will result in multiplying the monitor values with a ratio less than one, and thus produce lower forecasts at the grid cell than would result with the unscaled monitor data.

Temporal scaling is useful because monitors cannot provide any information about future conditions. Model data can provide this information, which can then be used to project future monitor concentrations.

Spatial and Temporal Scaling. Using both spatial and temporal scaling involves base-year and future-year air quality modeling files, and is simply a combination of spatial scaling and temporal scaling. BenMAP scales the concentrations of each neighboring monitor first by the ratio of the modeled concentration at the grid cell in the future year to the modeled concentration at the grid cell containing the monitor in the future year (spatial scaling), and then by the ratio of the modeled concentration at the grid cell containing the monitor in the future year to the modeled concentration at the grid cell containing the monitor in the base year (temporal scaling). Notice, however, that the two future year concentrations at the grid cell containing the monitor cancel out, allowing the ratio used to be simply the modeled concentration at the grid cell in the future year to the modeled concentration at the grid cell containing the monitor in the base year.

Adverse Health Effects

BenMAP is able to calculate the adverse health effects related to hundreds of health impact functions as part of the evaluation of the effects of various $PM_{2.5}$ (and other pollutant) air quality scenarios. It also comes with a wide variety of incidence rate data necessary to establish the baseline health conditions prior to calculating a change in health effects, and it allows for complex aggregation and pooling, in order to combine multiple sources of information. Finally it keeps track of all of the assumptions used in an analysis through the use of configurations that may be re-used and edited for new analyses.[6]

To calculate point estimates of the changes in incidence of a given adverse health effect associated with a given set of air quality changes, BenMAP performs a series of calculations at each grid-cell. First, it accesses the health impact functions needed for the analysis, and then it accesses any data needed by the health impact functions. Typically, these include the grid-cell population, the change in population exposure at the grid-cell, and the appropriate baseline incidence rate. It then calculates the change in incidence of adverse health effects for each selected health impact function. The resulting incidence change is stored, and BenMAP proceeds to the next grid-cell, where the above process is repeated.

BenMAP calculates the uncertainty surrounding estimated incidence changes, resulting from the sampling uncertainty surrounding the pollutant coefficients in the health impact functions used, and produce a distribution of possible incidence changes rather than a single point estimate. To do this, BenMAP uses an N-point Latin Hypercube to represent the underlying distribution, and creates a corresponding distribution of incidence changes in each population grid cell, where N is specified by the user (Helton and Davis, 2002).[7]

For pollutant-health endpoint combinations estimated by more than one health impact function, BenMAP can pool the incidence estimates using a variety of techniques, including fixed and random effects and user-specified subjective weights. The fixed effects model assumes that there is a single true concentration-response relationship and therefore a single true incidence estimate that applies everywhere. Differences among incidence estimates

[6] The sources of prevalence and incidence data included in BenMAP are documented in Appendix E of the User's manual (http://www.epa.gov/ttn/ecas/models/modeldoc.pdf), all PM-related concentration response functions packaged with BenMAP are documented in Appendix F, and Appendix I describes in detail the uncertainty and pooling options available to the user.
7 The Latin Hypercube method is used to enhance computer processing efficiency. It is a sampling method that divides a probability distribution into intervals of equal probability, with an assumption value for each interval assigned according to the interval's probability distribution. Compared with convention Monte Carlo sampling, the Latin Hypercube approach is more precise over a fewer number of trials because the distribution is sampled in a more even, consistent manner.

derived from different studies are therefore simply the result of sampling error. The certainty of an estimate is reflected in its variance (the larger the variance, the less certain the estimate). Fixed effects pooling therefore weights each incidence estimate in proportion to the inverse of its variance.

The weighting scheme used in a pooling based on the random effects model is basically the same as that used if a fixed effects model is assumed, but the variances used in the calculations are different. This is because a fixed effects model assumes that the variability among the estimates from different studies is due only to sampling error (i.e., each study is thought of as representing just another sample from the same underlying population), while the random effects model assumes that there is not only sampling error associated with each study, but that there is also between-study variability -- each study is estimating a different underlying concentration-response relationship. Therefore, the sum of the within-study variance and the between-study variance yields an overall variance estimate.[8]

Economic Cost

Once BenMAP has estimated the incidence associated with a particular health effect, derived from a single health impact function or multiple pooled health impact functions, the user may estimate the economic value of that incidence based on hundreds of preloaded health effect-specific dollar values. In the same way BenMAP estimates health effects, it can also estimate both point estimates of incidence valuation and a Latin Hypercube-based distribution of incidence valuation reflecting both the uncertainty surrounding estimated incidence and the uncertainty surrounding the unit values. BenMAP also allows for the pooling of endpoint specific valuation in the same way incidence estimates are pooled.[9]

Reporting

BenMAP has a number of reporting options to allow users to document their analyses. The user can sum across monetized benefits (to create estimates of total benefits associated with a given policy analysis) and can export incidence and valuation results to spreadsheet compatible files. The user has a set of mapping tools to visually inspect inputs and results, and to export maps to shapefile formats for use in other GIS programs. And the user has access to an audit trail that keeps track of all user’s decisions at each step of an analysis and to review decisions made in previous analyses.

BenMAP records each of the choices made when estimating the change in adverse health effects between a baseline and control scenario. This is referred to as a configuration. A configuration records the following choices: the air quality grids for the baseline and control scenarios; the year for the analysis; the threshold for the analysis; whether the analysis will focus on a single “point” estimate (Point Mode), or a range of results that mirror the variability in the inputs to the health impact functions (Latin Hypercube Points); the health impact functions to be used in estimating adverse health effects and associated pooling specifications; the unit values to be used in estimating the monetary value associated with the adverse health effects; and the pooling specifications used to estimate health effects and valuations based on more than one health impact function.

Once these choices are made, BenMAP saves the configuration file for future reuse. This is especially useful for recreating already existing policy analyses, such as those conducted by the U.S. EPA.

SAMPLE APPLICATIONS

We consider two sample applications. In the first, we analyze the benefits of a national-level air quality control program, and in the second, we examine the benefits associated with attaining two annual $PM_{2.5}$ standards in California, the national standard of 15 $\mu g/m^3$ and the more stringent California standard of 12 $\mu g/m^3$.

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[8] Appendix I of the BenMAP user’s manual provides the documentation and algorithms used for all weighting methods available to the user, including Fixed Effects and Random Effects weighting.
[9] Appendix H of the BenMAP user’s manual documents the source and derivation of all health effect unit values included in the software (http://www.epa.gov/ttn/ecas/models/modeldoc.pdf).

National-Level Benefits Example

As part of its congressional mandate, the U.S. EPA promulgates regulations to improve the nation's air quality, controlling emissions from both mobile and stationary sources. The Clean Air Act allows the EPA to set emissions standards to protect human health without regard to compliance cost. However, Executive Order 12866 requires federal agencies to estimate the benefits and costs of major new pollution control regulations. As a result, EPA presents the costs and benefits of all economically significant new rules in a Regulatory Impact Analysis.

The form of air quality regulations take many shapes to control criteria pollutants, such as PM and ozone, as well as hazardous air pollutants. The example presented here assumes the enactment of a national control strategy to reduce stationary sources of pollutant emissions related to the formulation of $PM_{2.5}$. We assume the rule would reduce emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x) from fossil fuel-fired combustion units by approximately 70 percent from current levels. These mandatory emission reductions would be achieved through a cap and trade program. Federally enforceable emissions limits, or national caps, for each pollutant would be established. Sources would be allowed to transfer these authorized emission limits among themselves to achieve the required reductions for all pollutants at the lowest overall cost.

Such an approach would likely provide significant benefits to public health and the environment. Emissions reductions would start before 2010 and would increase significantly between 2010 and 2020. The program would cut SO_2 emissions by 73 percent, from year 2000 emissions of 11 million tons to caps of 4.5 million tons in 2010 and 3 million tons in 2018. It would cut emissions of NO_x by 67 percent, from year 2000 emissions of 5 million tons to caps of 2.1 million tons in 2008 and 1.7 million tons in 2018. Based on these emissions reductions, the cumulative health benefits of the program across the next two decades are likely to be significant.

In order to characterize the health impacts and health-related economic benefits of the emission reductions likely to occur from implementation of a program such as the one above, EPA conducted sophisticated modeling of emissions reductions from electric utilities and the fate and transport of those emissions. EPA used the Integrated Planning Model (IPM) to estimate emissions changes and REMSAD to estimate changes in ambient levels of $PM_{2.5}$. In the following section, we demonstrate how BenMAP can be used to estimate population level exposure to changes in ambient $PM_{2.5}$, changes in incidence of key health effects, and the value of those changes in health.

BenMAP Analysis of a National-Level PM Control Program

To estimate $PM_{2.5}$ exposure for this example, the U.S. EPA used REMSAD modeling data, with a 36 kilometer by 36 kilometer resolution, to spatially and temporally scale 2001 $PM_{2.5}$ monitoring data. We use the same the same data as a starting point for our results.

Recall that to create air quality grids BenMAP scales the concentrations of each neighboring monitor first by the ratio of the modeled concentration at the grid cell in the future year to the modeled concentration at the grid cell containing the monitor in the future year (spatial scaling), and then by the ratio of the modeled concentration at the grid cell containing the monitor in the future year to the modeled concentration at the grid cell containing the monitor in the base year (temporal scaling). Figures 2, 3, and 4 display the 2001 monitoring data and the base year (2001) and future year (2020) modeling data used to create air quality grids for the air quality control program analyzed here. The resulting air quality grid is displayed in Figure 5.

We derived health impact functions using the available published scientific literature to ascertain the relationship between particulate matter exposure and adverse human health effects. In general, we selected health impact functions from epidemiological studies that: 1) used $PM_{2.5}$, 2) covered the broadest potentially exposed population, 3) had appropriate model specification (e.g. controlled for confounding pollutants), 4) had been peer-reviewed, and 5) analyzed health effects to which we could place an economic value.

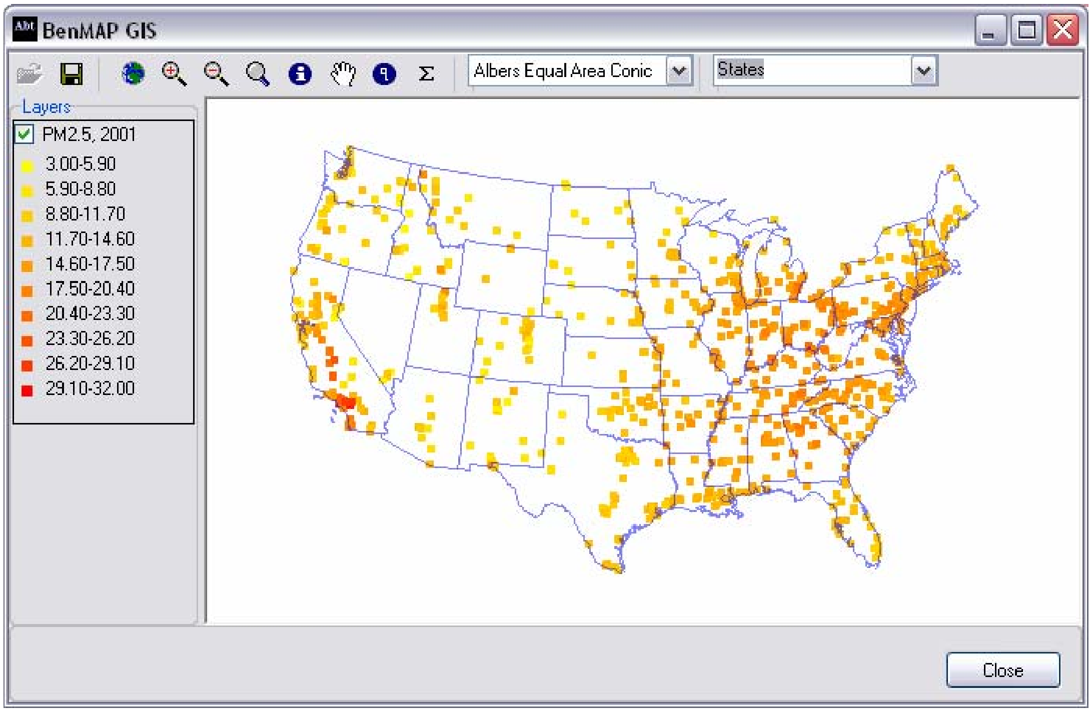

Figure 2. Year 2001 $PM_{2.5}$ monitors.

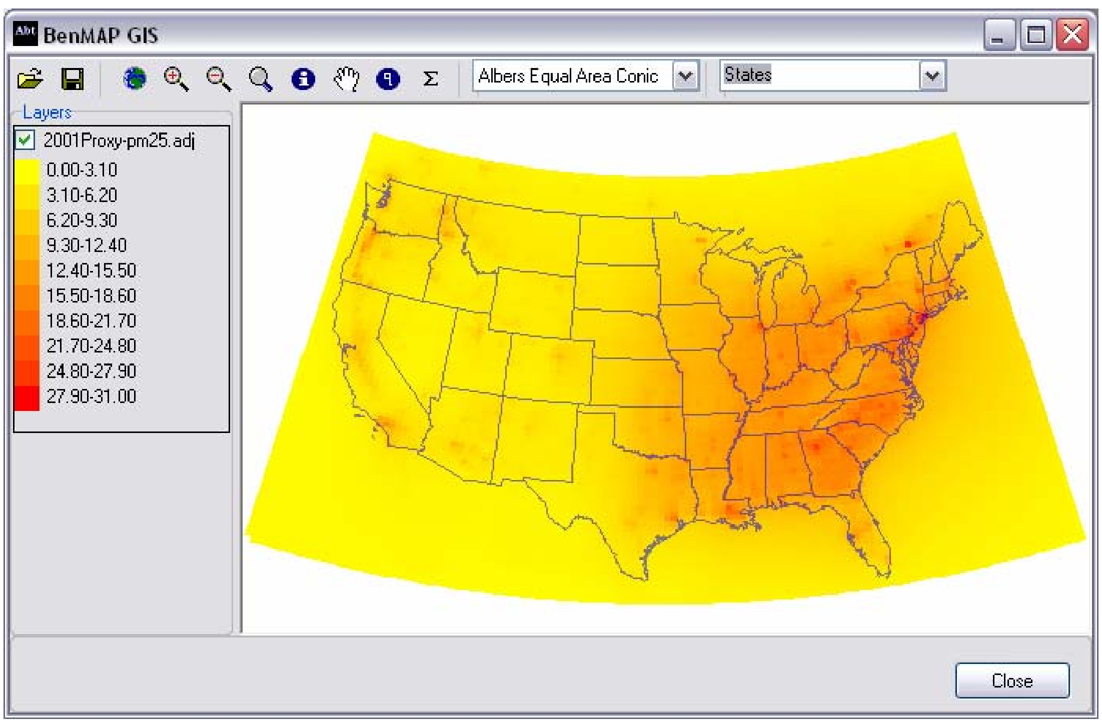

Figure 3. Base year (2001) REMSAD $PM_{2.5}$ modeling data used to spatially and temporally scale 2001 monitor data.

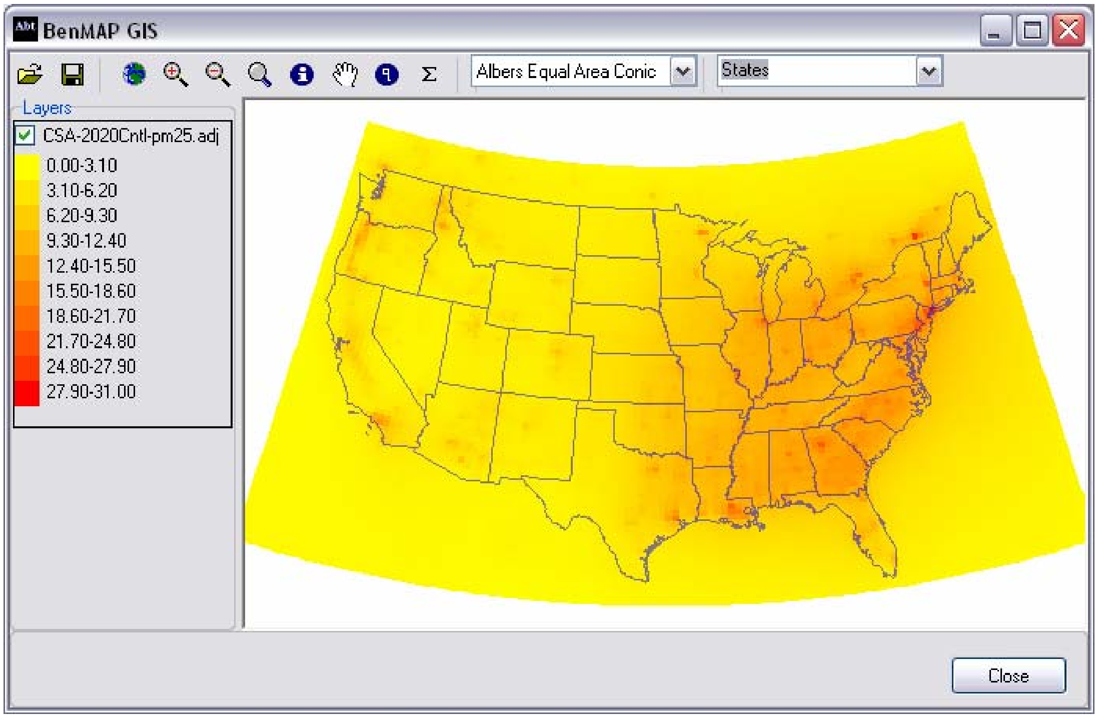

Figure 4. Future year (2020) REMSAD $PM_{2.5}$ modeling used to spatially and temporally scale 1001 monitor data.

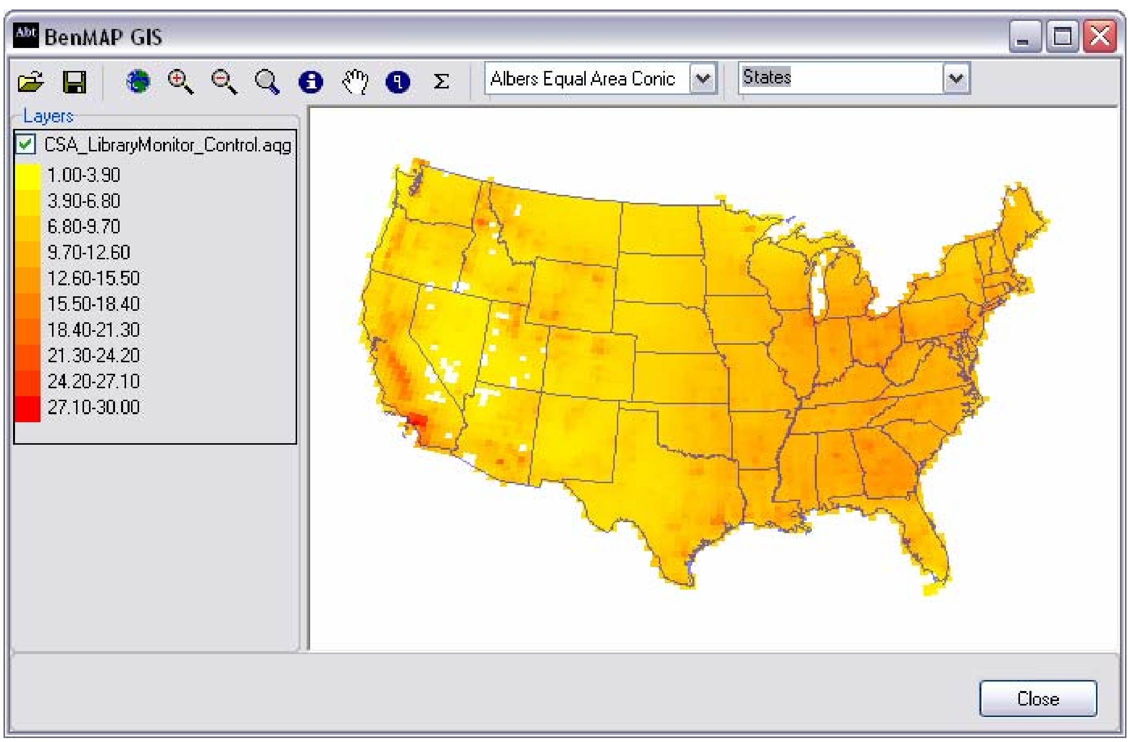

Figure 5. Scaled monitor data, reflecting a 2020 air quality scenario, interpolated to the REMSAD36 grid-cell level.

Table 2 lists a sample of the $PM_{2.5}$-related health impact functions used in the analysis, and the unit values that we used to estimate the monetary benefits. Table 3 presents the results of the analysis. Total benefits related to the selected $PM_{2.5}$ endpoints are approximately $114 billion (US 2000$), and are clearly dominated by the dollar benefits associated with premature mortality. Mortality, in fact, comprises 94 percent of total monetary benefits associated with the total. Though mortality dominates the economic valuation of benefits, BenMAP estimates many other adverse health effects that will be avoided in the future due to reductions related to the example national control scenario (Table 3).[10]

Table 2. Selected PM-related health effects and unit values.

Health Effect	Age	Epidemiological Study	$ /Case	Valuation Source
Mortality	30+	Krewski et al. (2000)	$6.0 million	Based on Viscusi (1992)
Chronic bronchitis	27+	Abbey et al. (1995)	$340,000	Based on Viscusi et al. (1991)
Non-fatal heart attacks	18+	Peters et al. (2001)	Vary by age	Based on Eisenstein et al. (2001) and Russell et al. (1998)
Respiratory Hospital Admissions	65+	Pooled estimate[a]: Moolgavkar (2000b) - ICD 490-496 Lippman et al. (2000) - ICD 490-496	$14,000	The cost-of-illness estimates (lost earnings plus direct medical costs) are based on ICD-9 code level information (e.g., average hospital care costs, average length of hospital stay, and weighted share of total category illnesses) reported in Agency for Healthcare Research and Quality, 2000 (www.ahrq.gov).
	18-64	Moolgavkar (2000b) - ICD 490-496 (less 493)	$12,000	
	65+	Lippman et al. (2000) - ICD 480-486	$18,000	
	<65	Sheppard, et al. (1999) - ICD 493	$8,000	
Cardiovascular Hospital Admissions	65+	Pooled estimate[a]: Moolgavkar (2000a) - ICD 390-429 (less 410) Lippman et al. (2000) - ICD 410-414, 427-428	$21,000	
	18-64	Moolgavkar (2000a) - ICD 390-429	$23,000	
Work loss days	18-64	Ostro (1987)	Vary by county	County-specific median annual wages divided by 50 (assuming 2 weeks of vacation) and then by 5 - to get median daily wage.
Minor restricted activity day	18-64	Ostro and Rothschild (1989)	$50	Based on Tolley et al. (1986)

[a] BenMAP generated pooled weights using the random/fixed effects approach.

Note that total benefits are the result of a dependent summation; summing across each individual endpoint's distribution of monetary benefits, we assume that the occurrence of a low (or high) estimate of incidence is shared across endpoints and that the occurrence of a low (or high) estimate of an endpoint's unit value is also shared across endpoints. The dependent summation assumption therefore makes it possible to sum across the 5th and 95th percentiles (or any other percentile).

[10] The quantified PM-related health effects presented here are a sample of those that BenMAP can quantify. Others include acute bronchitis, lower and upper respiratory illness, asthma exacerbations, respiratory symptoms, and infant mortality. Note that there are many other PM-related health effects that BenMAP is unable to quantify, but are known to be related to PM exposures, such as low birth weight, changes in pulmonary function, chronic respiratory diseases other than chronic bronchitis, etc.

Table 3. Selected $PM_{2.5}$-related health benefits associated with the national-level control scenario.

	Health Effects (cases)			Valuation (million 2000 $)[a]		
Health Effect	**5th**	**mean**	**95th**	**5th**	**mean**	**95th**
Mortality	8,100	14,000	20,000	15,300	107,000	261,000
Chronic Bronchitis	1,600	8,800	16,000	320	3,860	13,000
Heart Attacks	8,600	23,000	37,000	470	1,960	4,450
Resp Hosp Admissions	1,400	7,200	13,000	23	113	202
Cardio Hosp Admissions	-1,800	5,500	15,000	-39	124	316
Work Loss Days	1,400,000	1,600,000	1,800,000	182	208	235
Minor Restricted Activity Days	8,100,000	9,600,000	11,000,000	306	524	754
Total (dependent sum)	–	–	–	16,600	114,000	280,000

Note: For presentation purposes, the results were rounded.

[a] The benefits estimates include an adjustment to account for the growth in income over time, and a concomitant increase in willingness-to-pay for risk reduction.

In 2002, the Health Effects Institute (HEI) reported findings by health researchers at Johns Hopkins University and others raising concerns about aspects of the statistical methods used in a number of recent time-series studies of short-term exposures to air pollution and health effects (Greenbaum, 2002). Researchers found problems in the default "convergence criteria" used in Generalized Additive Models (GAM) and a separate issue about the potential to underestimate standard errors in the same statistical package. In response, the authors of studies affected by this problem began to reanalyze the results of several important time series studies to address these issues. In most, but not all, of the reanalyzed studies, it was found that risk estimates were reduced and confidence intervals increased. However, the reanalyses generally did not substantially change the findings of the original studies. At the time the authors conducted the case study presented here, the results of these reanalyses were not yet available.

Examination of the original studies used in this case study found that the PM-related health endpoints that were potentially affected by the GAM issues were limited only to reduced hospital admissions. All other quantified health effects, which account for over 99 percent of the total monetized benefits, were not affected by the GAM issue.

Attaining $PM_{2.5}$ Standard

In 1997, the U.S. EPA revised its National Ambient Air Quality Standards (NAAQS) for PM, as required under the Clean Air Act. The new standard required that monitored ambient $PM_{2.5}$ not exceed an annual average concentration of 15 $\mu g/m^3$. In response to their own pressing air quality problems, regulators in California set a more stringent annual $PM_{2.5}$ standard of 12 $\mu g/m^3$. Using the monitor rollback capabilities in BenMAP, we examined the benefits in California of attaining the national standard in 2002, as well as the extra benefits that California would achieve by attaining their more stringent State standard.

To estimate the benefits of the two standards, we used a population projection for 2002, aggregated the population data in a REMSAD grid of 36 kilometers by 36 kilometers, and then interpolated the monitor data using VNA with no maximum distance. Figure 6 displays the baseline air quality grid reflecting 2001 monitor data interpolated to the grid cell level. Also included on this Figure are the locations of all $PM_{2.5}$ monitors in California. Figure 7 presents the air quality associated with a rollback to 15 $\mu g/m^3$ for monitors that exceed the national standard, interpolated to the grid cell level. Figure 7 also displays the location of those monitors exceeding 15 $\mu g/m^3$ used in the rollback calculation. Figure 8 presents the air quality associated with a rollback to 12 $\mu g/m^3$ for monitors that exceed the more stringent standard, as well as the monitors used in the rollback calculation.

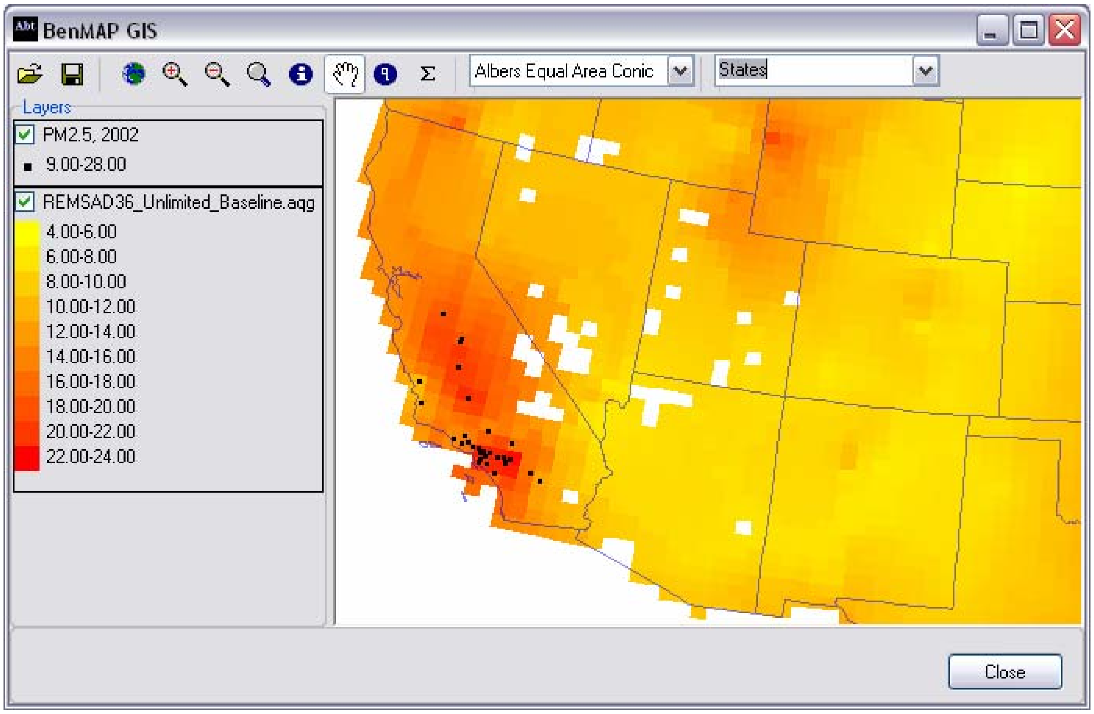

Figure 6. Baseline air quality grid reflecting 2001 monitor data interpolated to the grid cell level. Also included are the locations of $PM_{2.5}$ monitors in California.

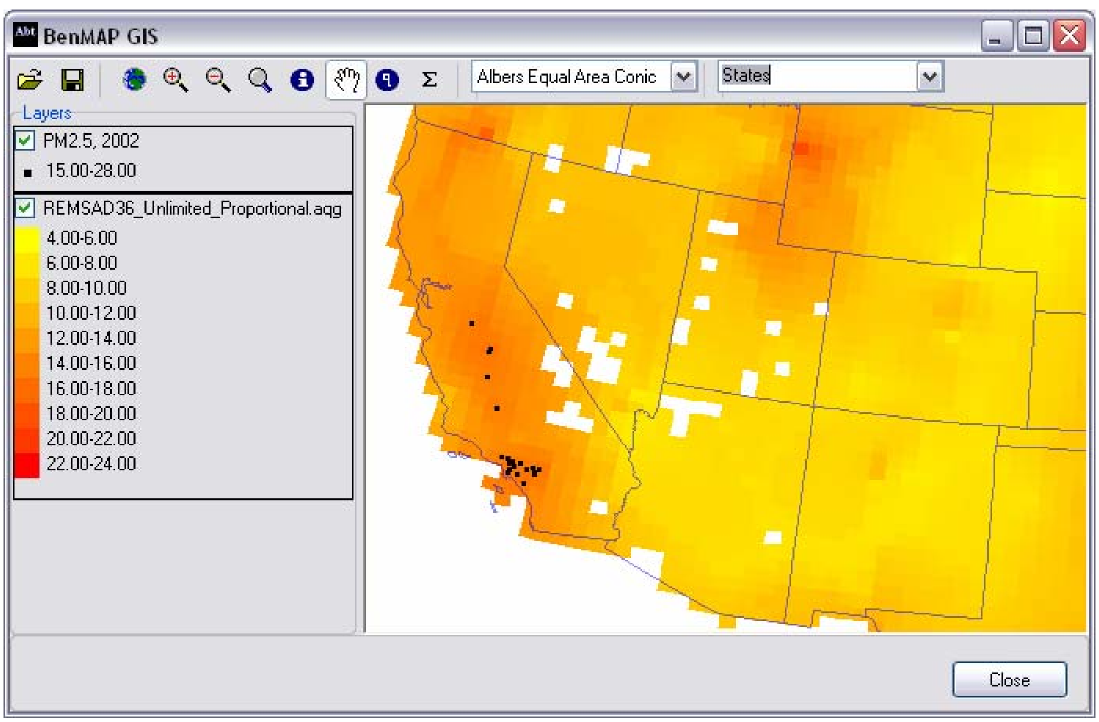

Figure 7. Air quality associated with a rollback to 15 μg/m^3 for monitors that exceed the national standard, interpolated to the grid cell level. Also included are the locations of those monitors exceeding 15 μg/m^3.

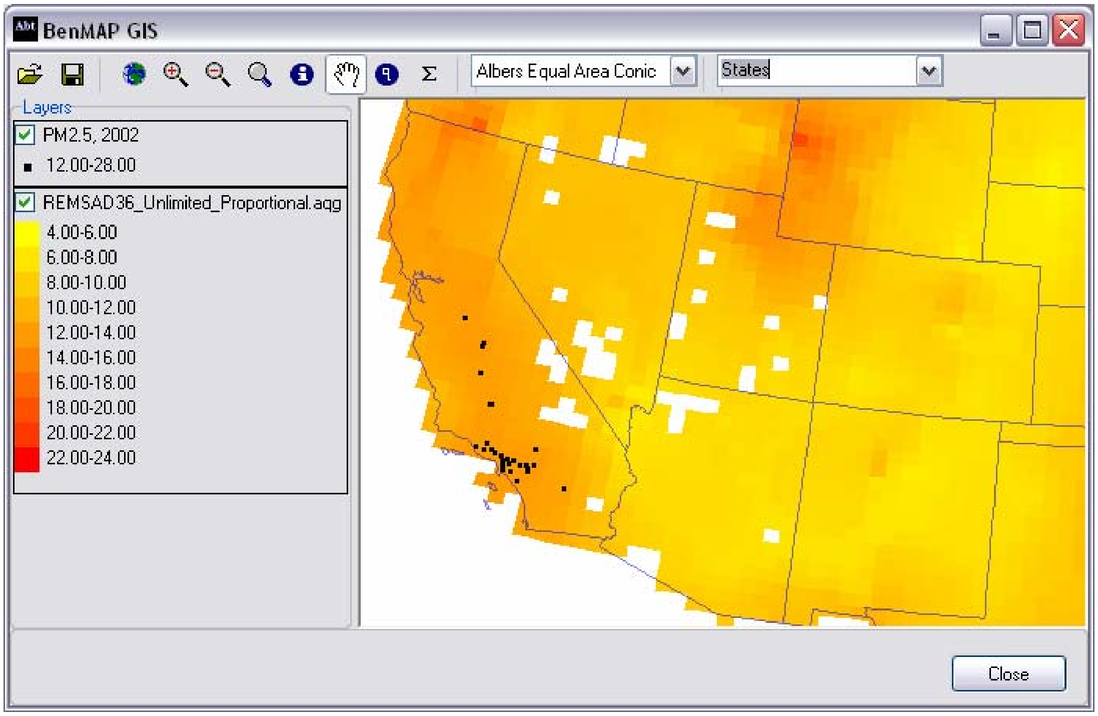

Figure 8. Air quality associated with a rollback to 12 μg/m^3 for monitors that exceed the California standard, interpolated to the grid cell level. Also included are the locations of those monitors exceeding 12 μg/m^3.

Table 4 presents the results of the analysis. The reduction in deaths associated with meeting the 15 μg/m^3 is substantial, and further lowering of the standard results in an additional 50 percent reduction. As expected, the results are sensitive to whether we used a proportional rollback or a quadratic rollback. Results are particularly sensitive to the maximum distance that we used to exclude monitors. Setting a maximum distance of 10 kilometers reduced the benefits by half. The type of grid that we used had some effect, with the smaller grid size producing a larger impact, presumably because the smaller grid is better able to capture "hot spots" with particularly high $PM_{2.5}$ levels.

Table 4. Reduction in premature mortality associated with achieving alternative annual $pm_{2.5}$ standards in California.

Grid	Max Monitor Distance	Rollback Type	Deaths Avoided by Attaining 15 μg/m^3 Standard	Additional Deaths Avoided by going from 15 to 12 μg/m^3 standard
REMSAD36	Unlimited	Proportional	5,100	2,800
REMSAD36	Unlimited	Quadratic	4,300	1,700
REMSAD36	10 km	Proportional	2,400	1,100
REMSAD36	50 km	Proportional	4,200	2,100
REMSAD12	Unlimited	Proportional	5,200	2,900
County	Unlimited	Proportional	4,000	2,500

Note: For presentation purposes, the results were rounded.

DISCUSSION

Environmental problems are increasingly a concern, and it is useful to have tools to analyze the magnitude of the problem and the benefits that may be achieved by policies to reduce the threat. BenMAP provides a useful to tool to analyze a range of air pollution problems. In particular, we have used it to estimate the benefits of reducing $PM_{2.5}$ levels through a national-level PM control program, and then to estimate the benefits of achieving alternative annual $PM_{2.5}$ standards in California.

BenMAP provides the user with a quick and flexible approach to estimating air pollution exposure, the associated health effects, and the economic benefits of avoiding these effects. In addition, it provides powerful mapping functions, the ability to characterize the uncertainty arising from the concentration-response coefficient and the unit value assigned to each health effect, and tools to aggregate and pool results in multiple ways. Another key feature of BenMAP is its transparency. BenMAP keeps track of all of the assumptions used in the analysis, allowing a user to easily replicate previous analyses, and to track the assumptions that others have made in their analyses. Through a command-line version of BenMAP, a user may also skip the graphical user interface in BenMAP, and generate the results for any number of sensitivity tests with a batch file.

The estimated benefits for the various scenarios that we have considered are significant, and highlight the serious nature of air pollution. It also highlights the usefulness of providing easily accessible results to policy makers and stakeholders. And at the same time, it makes clear the range of assumptions that underlie these types of analyses, and the need to adequately consider the inherent uncertainty and variability.

Sources of uncertainty in results

As in most complex analyses, there are many sources of uncertainty that affect the final benefits estimates. These include the emission inventories, air quality models (with their associated parameters and inputs), estimates of the future state of the world (i.e., regulations, technology, and human behavior), population estimates, epidemiological estimates of health impact functions, and estimates of dollar values per health effect, among others. For some parameters or inputs it may be possible to provide a statistical representation of the underlying uncertainty distribution. For other parameters or inputs, the necessary information is not available.
In our quantified estimate of uncertainty we have captured only two sources of uncertainty. We have quantified an estimate of uncertainty associated with the health impact function and with the valuation of adverse health effects. However, we have not included other sources of uncertainty such as in the estimation air quality, population exposure, incidence rates, and others. As a result the confidence interval can be misleading. However, it does provide at least some information about the impact of those two sources of uncertainty on the likely range of benefits.

In addition to being uncertain, the true magnitude of the benefits is also inherently variable due to the truly random processes that govern pollutant emissions and ambient air quality in a given year. Factors such as hours of equipment use and weather display constant variability regardless of our ability to accurately measure them. As such, the estimates of annual benefits generated by BenMAP should be viewed as representative of the magnitude of benefits expected, rather than the actual benefits that would occur every year.

There are a number of key assumptions that affected the calculation of our results, and how they should be interpreted. We have assumed that all types of $PM_{2.5}$ are equally harmful. While this is a reasonable interpretation of the epidemiological evidence, we note that the evidence is not definitive regarding the impacts of size and composition of particles. It could be that future research may point to certain particle types as being especially harmful, and the results of the present analysis would be substantially different. A second key assumption is in regards to the estimation and valuation of premature mortality. To estimate premature mortality, we have used a re-analysis by Krewski et al. (2000) of the American Cancer Society cohort. If we had used a daily time-series study such as that used by Burtraw et al. (2003, p. 658), our benefits estimate would have been lower by roughly a factor of three, and if we had valued mortality using the results from Mrozek and Taylor (2002) our estimate would have been reduced by another factor of three.

However, based on current advice from a number of scientific panels, we have chosen to rely on cohort epidemiological studies measuring the impact of long term exposure to $PM_{2.5}$ (U.S. EPA, 2001; National Research Council, 2002) and on an estimate of the value of statistical life consistent with the broader set of contingent valuation and hedonic wage literature (U.S. EPA, 2000). Finally, we have applied concentration-response functions only to the specific populations covered by the samples in the underlying epidemiological studies. In many cases, these samples were based solely on convenience (e.g., hospital discharge data from Medicare is limited to populations over 65) rather than on expectations about the populations potentially at risk. This assumption will lead to an underestimation of the total health impacts associated with a given $PM_{2.5}$ reduction.

Future directions for BenMAP

The U.S. EPA is actively developing BenMAP to better characterize uncertainty and the key assumptions that drive the estimated benefits, develop better databases, and increase the public's ability to access BenMAP and the databases used in any given analysis. The improved databases will include additional monitoring data (including speciated $PM_{2.5}$), more spatially disaggregated estimates of incidence and prevalence (as well as projections of incidence and prevalence). Uncertainty will be improved in several respects, such as by including the uncertainty in incidence and prevalence estimates, including more structured correlation patterns between the available distributions, more systematic influence analysis tools, and incorporating some limited tests of the uncertainty in air quality. Finally, U.S. EPA has made BenMAP available on the web, along with the databases and assumptions used in their analyses of air regulations, in order to make the policy analysis process as transparent as possible. Interested users can download BenMAP at http://www.epa.gov/ttn/ecas/benmapdownload.html.

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