Front. Environ. Sci. Eng. 2015, 9(6): 1056–1065
DOI 10.1007/s11783-015-0796-8

RESEARCH ARTICLE

Development of an integrated policy making tool for assessing air quality and human health benefits of air pollution control

Xuezhen QIU[1], Yun ZHU (✉)[1], Carey JANG[2], Che-Jen LIN[1,3], Shuxiao WANG[4], Joshua FU[5], Junping XIE[1], Jiandong WANG[4], Dian DING[1], Shicheng LONG[1]

1 Guangdong Provincial Key Laboratory of Atmospheric Environment and Pollution Control, College of Environment and Energy, South China University of Technology, Guangzhou Higher Education Mega Center, Guangzhou 510006, China
2 USEPA/Office of Air Quality Planning & Standards, RTP, NC 27711, USA
3 Department of Civil Engineering, Lamar University, Beaumont, TX 77710-0024, USA
4 State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Tsinghua University, Beijing 100084, China
5 Department of Civil & Environmental Engineering, University of Tennessee, Knoxville, TN 37996-2010, USA

Abstract Efficient air quality management is critical to protect public health from the adverse impacts of air pollution. To evaluate the effectiveness of air pollution control strategies, the US Environmental Protection Agency (US EPA) has developed the Software for Model Attainment Test-Community Edition (SMAT-CE) to assess the air quality attainment of emission reductions, and the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) to evaluate the health and economic benefits of air quality improvement respectively. Since scientific decision-making requires timely and coherent information, developing the linkage between SMAT-CE and BenMAP-CE into an integrated assessment platform is desirable. To address this need, a new module linking SMAT-CE to BenMAP-CE has been developed and tested. The new module streamlines the assessment of air quality and human health benefits for a proposed air pollution control strategy. It also implements an optimized data gridding algorithm which significantly enhances the computational efficiency without compromising accuracy. The performance of the integrated software package is demonstrated through a case study that evaluates the air quality and associated economic benefits of a national-level control strategy of $PM_{2.5}$. The results of the case study show that the proposed emission reduction reduces the number of nonattainment sites from 379 to 25 based on the US National Ambient Air Quality Standards, leading to more than US$334 billion of economic benefits annually from improved public health. The integration of the science-based software tools in this study enhances the efficiency of developing effective and optimized emission control strategies for policy makers.

Received March 4, 2015; accepted May 18, 2015

E-mail: zhuyun@scut.edu.cn

Keywords air quality assessment, human health benefit, economic benefit, air quality attainment assessment, air pollution control strategy, decision support system

1 Introduction

Air pollution has adverse health effects including premature mortality [1–3], morbidity of cardiovascular diseases [4] and respiratory problems [5,6]. The World Health Organization (WHO) estimates that ambient air pollution causes 3.7 million deaths in 2012, which include 40% ischemic heart disease, 40% stroke, 11% chronic obstructive pulmonary disease (COPD), 6% lung cancer, and 3% acute lower respiratory infections in children [7]. Therefore, improving air quality through emission control is critical to protect public health.

Air quality management is a practice that evaluates emission reduction options to achieve a desired air quality standard in many countries [8]. To determine the emission reduction goals, careful considerations must be given to the effectiveness of emission control, the cost of the control technologies as well as the economic and social benefits of air quality improvement [9]. Based on the analysis of costs and benefits, policy makers can implement the most effective control strategy to protect the public health. Such assessment process typically involves air quality simulations using complex atmospheric models, massive data processing of model output, and complicated cost-benefit analysis [10]. Therefore, a suite of software tools is needed to facilitate the process of air quality management.

A number of software tools for air quality management have been developed by US EPA to address the analytical needs. These include (available at www.abacas-dss.com): (1) the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) for evaluating human health and economic benefits associated with improved air quality [11]; (2) the Software for Model Attainment Test-Community Edition (SMAT-CE) for attainment test of the ambient air quality standard under various air pollution control strategies [12]; (3) the Response Surface Model-Visualization Analysis Tool (RSM-VAT) for real-time estimates of air quality concentrations caused by air emission reduction [13]; (4) the Multi-Pollutant Control Cost Model (CoST CE) for evaluating the cost of emission control technologies to achieve specified emission reduction goals [14]. These tools operate in a stand-alone fashion and require further integration to streamline the process of air quality management.

This study presents an integrated assessment platform incorporating SMAT-CE and BenMAP-CE, and demonstrates the application of the integrated software tools for evaluating air quality attainment and the health and economic benefits of emission control.

2 Development of software integration

2.1 Development of linkage between SMAT-CE and BenMAP-CE

The integrated assessment process of SMAT-CE and BenMAP-CE is illustrated at Fig. 1. The integrated assessment platform aims to conduct the air quality attainment for an air pollution control strategy first, and then seamlessly evaluate the correlated human health and economic benefits. Combining the modeled and observational input data, SMAT-CE predicts (1) the future-year air quality data at each monitoring site for air quality attainment test, and (2) the base-year and future-year air quality data in each model grid (such as at 12km × 12km spatial resolution) for further analysis in BenMAP-CE. With the base-year and future-year air quality input data, BenMAP-CE can calculate the human health and economic benefits due to the air quality improvement. Other necessary input data/ choices for the health and economic benefits analysis include population data, incidence rate data, health impact functions, and valuation functions, are contained in the BenMAP-CE database.

The gridded air quality data generated by SMAT-CE cannot be directly applied as input to BenMAP-CE because of two differences in data format: (1) the gridded data of SMAT-CE are point values (at one point of each grid cell, e.g., the centroid), while the air quality input data for BenMAP-CE need areal values; (2) the gridded data of

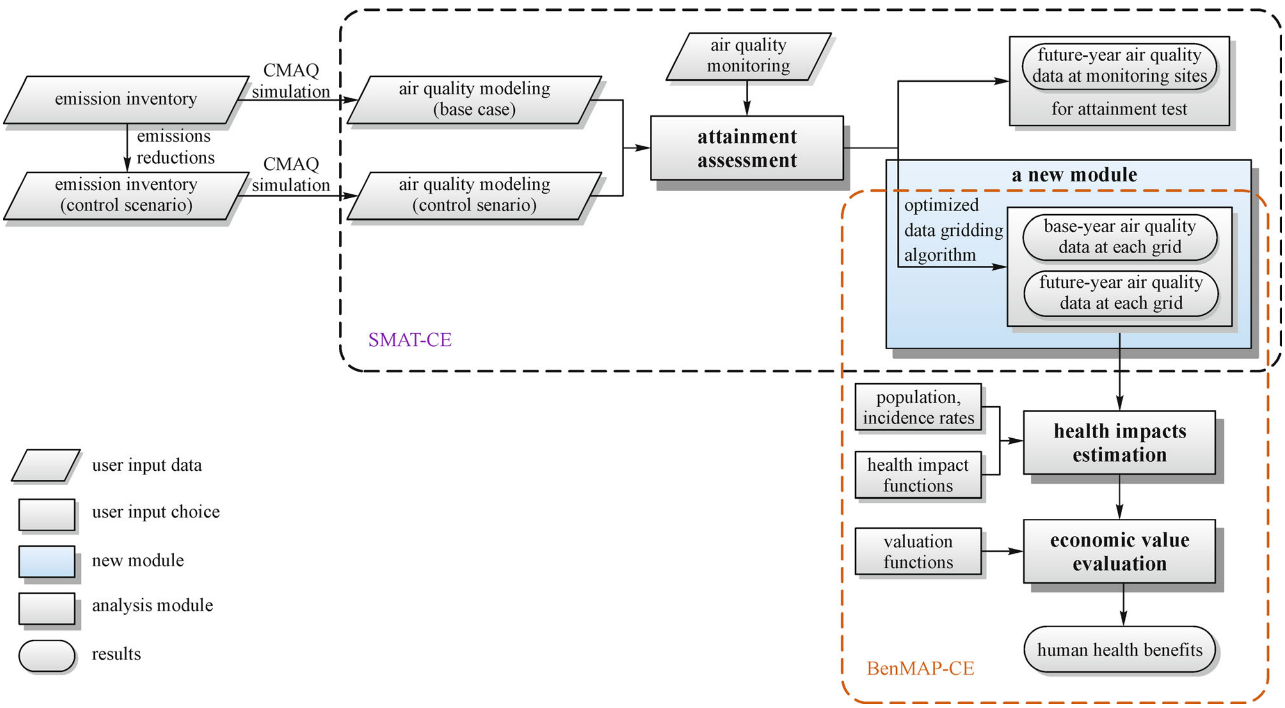

Fig. 1 Development of linkage between SMAT-CE and BenMAP-CE to sequentially evaluate air quality and correlated health and economic benefits of proposed emissions reductions

SMAT-CE lack several fields needed for BenMAP-CE. To bridge the data gap, a new module is developed to achieve efficient data conversion. It performs a GIS spatial join process to convert the point-based data to the area-based data, which includes several steps: (1) user imports an appropriate shape file (its spatial resolution should be consistent with the one of SMAT-CE result) to provide grid information; (2) the program changes the shape file projection to "Lambert," captures the centroid of each grid cell based on the corresponding method provided by DotSpatial [15], and records the coordinate of each centroid; (3) for each target point in SMAT-CE result, the program gets the nearest centroid and assigns the grid information of this centroid to it. Through the above steps, the point-based air quality data can be converted to an area-based one. After that, additional fields which specify the type (such as annual average, quarterly average, daily) of the air quality data file are added to the converted data file. There are three fields needed: metric for defining daily average/ 8-h max/ 1-h max etc., seasonal metric for defining quarterly average or not, and annual metric for defining annual average or not. For example, the metric, seasonal metric and annual metric should be "daily average", "quarterly average" and "annual average" for annual $PM_{2.5}$ data, and "daily average", "null" and "null" for daily $PM_{2.5}$ data.

In the newly developed module, a new data interface is also included to speed up the data retrieval and transfer between SMAT-CE and BenMAP-CE. Take annual $PM_{2.5}$ as an example, after SMAT-CE generates BenMAP-ready input data, a linking button is provided in the result viewer page to link to BenMAP-CE. Once user clicks this button, SMAT-CE will start the BenMAP-CE program in the background, and a linking window will appear for user to select the analysis pollutant and data grid type from the correlated values in BenMAP-CE database. When these two settings are completed, the air quality results data will be automatically loaded into BenMAP-CE. After that, user can set other options (e.g., population data, health impact functions) and then run the configuration to get the health and economic benefits results.

2.2 Air quality benefits assessment

SMAT-CE is an updated tool upon Modeled Attainment Test Software (MATS) [16] to demonstrate the effectiveness of air emission reduction proposed in the state implementation [17] for meeting the National Ambient Air Quality Standards (NAAQS) and the Regional Haze Rule. In this study, the term "attainment" refers to meeting the air pollutant concentration limit as specified in the NAAQS. SMAT-CE uses statistical methods to combine observational and modeled data for air quality attainment assessment at air monitoring sites and grid cells. The methodology and algorithm have been described in details in Wang et al. [12]. Briefly, the future-year pollutant concentration at a specific site (a monitoring site or grid cell) is predicted using a base-year observational data and the modeled data obtained from the base-year and future-year air quality simulations. The future-year pollutant concentration is estimated as the product of the base-year monitoring value (ppb or $\mu g \cdot m^{-3}$) and the concentration ratio of future-year modeled value to base-year one (unitless). The estimated results include (1) future-year pollutant concentrations at monitoring sites for conducting NAAQS attainment test and (2) spatial distribution of pollutant concentration for analyzing regional air pollution.

A data gridding algorithm provided by DotSpatial [15] is employed to calculate weighted pollutant concentration at each grid cell in SMAT-CE, since not every grid cell contains a monitoring site. The calculation is based on those base-year observational values. For each grid cell, the algorithm first identifies neighboring monitors by drawing Thiessen polygons, and then calculates a weighted average value from these neighboring observational values by a factor of distances or square of the distances [15]. In the standard algorithm provided by DotSpatial, the Thiessen polygons are drawn with low efficiency in the whole domain. In this work, we performed an optimization to the standard data gridding algorithm. We define a limited circular area (center: grid cell centroid; radius: about 1665km) rather than the whole domain to perform the drawing process. As a result, this optimization shortens the computational time of interpolation process from 190.2 min to 49.7 min (by 73%) in the case study. To ensure the accuracy and reliability of the gridded pollutant concentration results generated by the improved algorithm, the results are compared to those produced by the standard algorithm using the same input data and configurations. The mean normalized bias (*MNB*) is utilized for the comparison:

$$MNB = \frac{1}{N}\sum_{i=1}^{N}\frac{C_m - C_0}{C_0}, \tag{1}$$

where N is the number of monitoring sites, C_m is the predicted pollutant concentration

produced by the improved algorithm at site i, and C_0 is the predicted pollutant concentration produced by standard algorithm at site i. The comparison shows that the improved algorithm can replicate the estimated results of the standard algorithm with a *MNB* of −0.0085% (Fig. 2 (a)). Fig. 2(b) shows the spatial difference of the two data sets, which is indistinguishable in the study area (the conterminous US).

2.3 Health and economic benefits evaluation

BenMAP-CE is a software tool improved upon legacy BenMAP [18]. It can estimate human health and economic benefits associated with air quality improvement. The

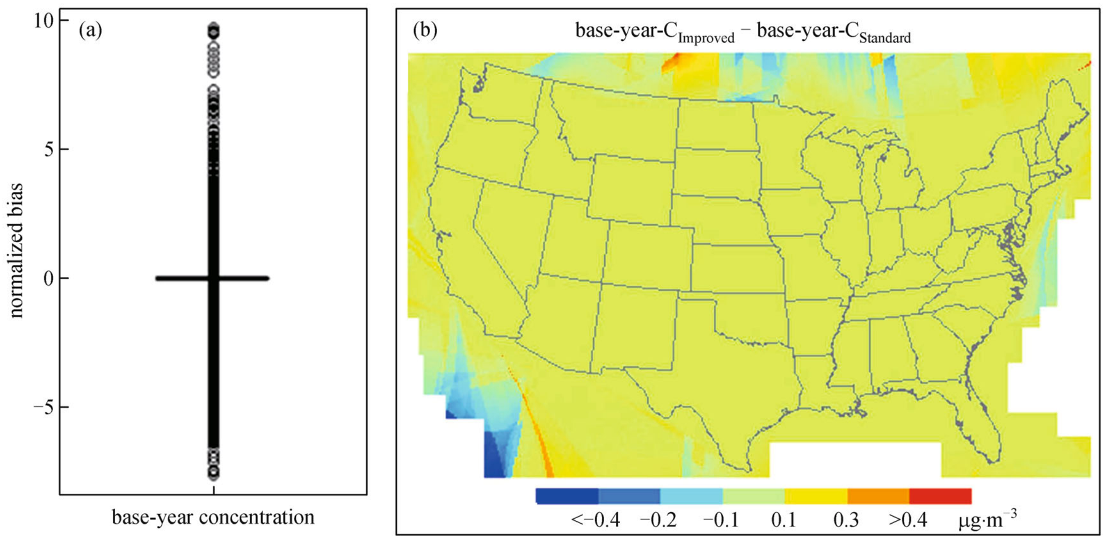

Fig. 2 Comparison of the base-year pollutant concentration generated by the improved algorithm and the standard algorithm (sample = 89308): (a) distribution of the normalized bias, (b) spatial difference of the pollutant concentration

algorithm and implementation of BenMAP-CE are described in details elsewhere [11,19]. The evaluation process is based on the data of a base and a future year air quality, population, incidence of disease (such as premature mortality) and algorithms that define the cost of health impact and valuation [11]. The quantification of human health and economic benefits is accomplished through three major steps. In the first step, BenMAP-CE calculates the changes in ambient air quality using either base-year and future-year modeled or observational data. Next, it estimates the health impact changes of selected health endpoints (such as premature death, chronic bronchitis, and acute respiratory symptoms) due to air quality improvement. The quantification of health impact changes is based on the health impact functions. A log-linear health impact function can be written as:

$$\Delta Y = Y_0(1-e^{-\beta\Delta C})\times Pop, \tag{2}$$

where ΔY is the estimated change in the health impacts due to the pollutant concentration change, Y_0 is the baseline incidence of the health endpoint, β is the coefficient of association between pollutant concentration and health impact, ΔC is the estimated change of pollutant concentration, Pop is the size of exposed population. The baseline incidence rates and exposed population data are contained in the BenMAP-CE database. The incidence rates are calculated based on the statistical data obtained from the Centers for Disease Control, National Center for Health Statistics, Healthcare Cost and Utilization Project, other association (such as American Lung Association) or correlated studies in the US Most of the initial data are presented in the user's manual appendices of BenMAP-CE [20]. Take the all-cause mortality rate (per year) as an example; the national average rate is 0.00015 for those people older than 85 in 2020. The population data in BenMAP-CE is built on the block-level data from 2010 US Census, and county-level population predictions of each year from 2000 to 2040 (can be converted to other level, such as state) [20].

Finally, BenMAP-CE evaluates the economic value as the product of the health impact reduction (case) and health effect-specific dollar value (US$ per case). Each record of health impact or economic result contains a single point estimate and a distribution of possible values due to the uncertainty resulting from the sampling surrounding the pollutant coefficients of health impact function or valuation function. For the estimated results (different health impact functions) of the same health endpoint, BenMAP-CE allows to pool them to achieve study-specific estimates synthesis or reduce the uncertainty of results with larger sample size. A variety of pooling approaches are provided in BenMAP-CE, including sum, subtraction, fixed effects and random/ fixed effects weights etc. [21]. In addition, the estimated results can be aggregated between different data grids (e.g., county, state, and nation).

BenMAP-CE provides a series of visualization analyses for health impact estimates and economic benefits: (1) "GIS" tab for mapping result in different levels (e.g., county, state, and nation), (2) "Data" tab for detail information, (3) "Chart" tab for graphical presentation, (4) "Cumulative Distribution Function (CDF) graphs" tab for uncertainty distribution, and (5) "Configuration" tab for recording user-specified settings. They are combined in a result-displaying area, which is integrated in the main window, providing users an easy-to-use operation interface.

3 Application of the integrated policy making tool

3.1 Case study

A US test case is performed to examine the performance of the integrated software tool. In the case study, $PM_{2.5}$ is selected as the test pollutant and the selected control strategy is 25% NO_x reduction, 25% SO_2 reduction, 100% reduction on residential wood combustion and 50% $PM_{2.5}$ reduction from non-EGU (Non-Electric Generating Units) of the emission levels in 2007. The annual $PM_{2.5}$ concentration in the NAAQS is specified as $12 \mu g \cdot m^{-3}$, which is required to be achieved by 2020 in the conterminous US Therefore, the base year is 2007 and the targeted control year is 2020. The simulated output using CMAQ is applied for this evaluation. The CMAQ results have been verified, which indicates that the model is capable of simulating the annual $PM_{2.5}$ with a *MNB* of -18% (Fig. 3).

Using the observational (2007) and modeled data (2007 and 2020) of $PM_{2.5}$, SMAT-CE projects the $PM_{2.5}$ concentrations in 2020 at the monitoring sites. The data are then utilized to determine the level of compliance to air quality standard. Based on the proposed emission reduction, the number of nonattainment sites ($PM_{2.5} > 12 \mu g \cdot m^{-3}$) is predicted to be 25 in 2020 as compared to 379 in 2007. The majority of the non-attainment sites will be located in California (22 out of 25, Fig. 4).

After the attainment test, the assessment platform exports the gridded air quality estimates by SMAT-CE to BenMAP-CE for health and economic benefits analysis. Accordingly, we choose health impact functions (HIFs) from epidemiological studies that meet four quality standards: (1) use $PM_{2.5}$ concentrations as primary exposure pollutant, (2) cover the potentially exposed

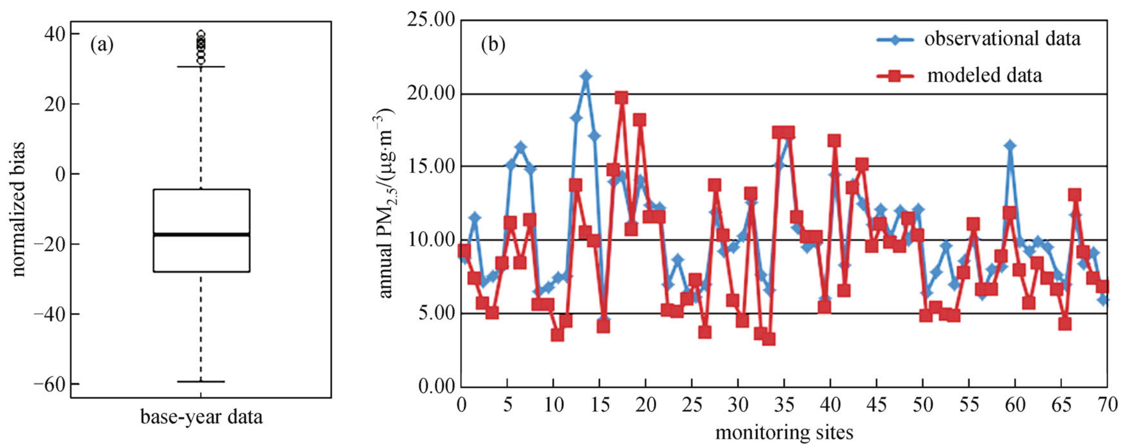

Fig. 3 Comparison of the base-year modeled and observational annual $PM_{2.5}$ concentrations at all the monitoring sites within the US: (a) distribution of the normalized bias, (b) variation patterns of those values at monitoring sites within California

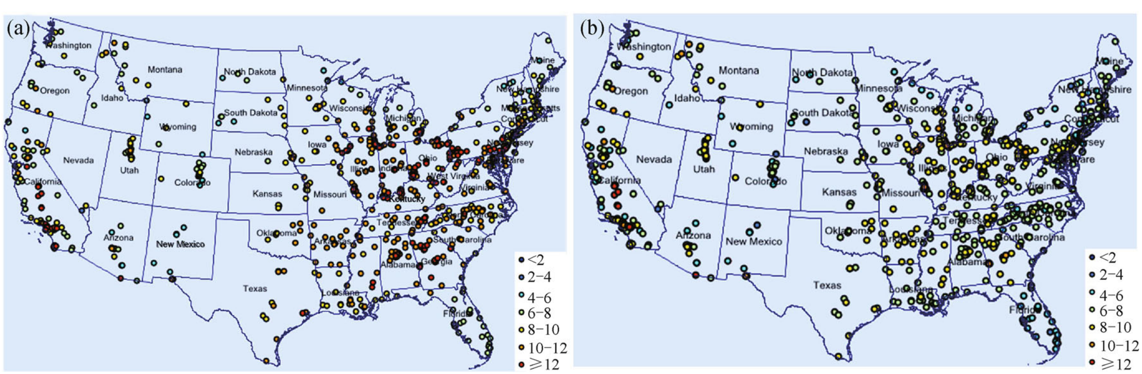

Fig. 4 Attainment test results of annual $PM_{2.5}$ under the proposed air pollution control strategy: (a) distribution of annual $PM_{2.5}$ concentration at each monitoring site in 2007 ($\mu g \cdot m^{-3}$), (b) distribution of annual $PM_{2.5}$ concentration at each monitoring site in 2020 ($\mu g \cdot m^{-3}$); the air pollution control strategy includes 25% NO_x reduction, 25% SO_2 reduction, 100% reduction on residential wood combustion and 50% $PM_{2.5}$ reduction from non-EGU (Non-Electric Generating Units) of the emission levels in 2007

population, (3) present appropriate model specification (e. g., controlling for confounding pollutants), and (4) be published in peer-reviewed journal. Table 1 lists the selected $PM_{2.5}$-related HIFs used in the analysis, and the valuation methods used to estimate the monetary values. We select "fixed effects" [21] as the pooling method for the health impact functions with the same health endpoint and age range. This pooling method weights each incidence estimates in proportion to the inverse of its variance, since the fixed effects model assumes that there is a single true concentration-response relationship and the differences among incidence estimates from different studies are therefore simply the result of sampling error.

Table 2 presents the health and economic benefits results of each health endpoint based on the selected health impact functions and valuation functions listed in Table 1. The total economic benefits of the improved air quality caused by the lower $PM_{2.5}$ concentration are estimated to be more than US$334 billion. The monetary benefit is primarily contributed by the decrease of premature mortality ($>95\%$), consistent with earlier studies [18,19]. The distribution of monetary health benefits is displayed in Figs. 5(a) and 5(b). Based on the proposed emission reductions, California, New York and Pennsylvania are the three states that benefit the most from the improved air quality. Additional details of each health endpoint are also available in the data results/ files prepared by the software tool. For example, New York has the largest reductions on hospital admissions and emergency room visits, while California benefits the most in almost all other health endpoints. The distribution of monetary health benefits (Fig. 5(b)), air quality benefits (Fig. 5(c)) and population data (Fig. 5(d)) suggests that high economic benefits are proportional to large population and (almost) to the great change in pollutant concentration, which is also indicated by Eq. (2).

Combining the air quality benefits and related health and economic benefits, policy maker can determine the more optimal control approach from specific emission control alternatives. Here the "more optimal control approach" refers to the control scenario whose air quality can attain the target/ standard and economic benefits are the largest in all the emission control alternatives. Users also have the option to further improve a control strategy through synthesis analysis of the predicted future-year air quality and a science-specific ratio of the health (economic) benefits to air quality (AQ) benefits. The distribution of predicted air quality in 2020 is presented in Fig. 6(a), and the health/AQ benefit ratio in each state is displayed in Fig. 6(b). In the case study, for the regions where the future-year annual $PM_{2.5}$ concentration is far below the NAAQS ($< 7.2\ \mu g \cdot m^{-3}$) (e.g., West Virginia, Virginia) and the ratio is low, the emission reduction rate can be cut down. Instead, for the nonattainment state with high ratio (e.g., California), the emission reduction rate should be increased in main sources (local or regional) to achieve

Table 1 Selected PM-related health impact functions for analyses

Health endpoints	start age	end age	epidemiological study	valuation method[a)]
mortality, all cause	25	99	Krewski et al. [22]	value of statistical life
	0	1	pooled estimate[b)]: Woodruff et al. [23] Woodruff et al. [24]	
respiratory hospital admissions	65	99	pooled estimate[b)]: Zanobetti et al. [25] Kloog et al. [26]	cost of illness
	18	64	Moolgavkar [27]	
	0	17	Babin et al. [28]	
cardiovascular hospital admissions	65	99	pooled estimate[b)]: Bell et al. [29] Bell [30]	
	18	64	Moolgavkar [31]	
chronic bronchitis	27	99	Abbey et al. [32]	
acute myocardial infarction, non-fatal	18	99	Zanobetti et al. [25]	
asthma emergency room visits	0	99	pooled estimate[b)]: Slaughter et al. [33] Mar et al. [34] Glad et al. [35]	
acute bronchitis	8	12	Dockery et al. [36]	willing to pay
asthma exacerbation	6	18	Ostro et al. [37]	
acute respiratory symptoms	18	64	Ostro and Rothschild [38]	

Notes: a) the valuation methods are selected from BenMAP-CE database depends on the health endpoint and its age range; b) the pooling method is "fixed effects"

Table 2 Total annual monetary valuations of the national air pollution control strategy (health impacts rounded to the nearest integer, and economic values rounded to the nearest million US$) [95% confidence interval]

health endpoints	health impacts/(hundred cases) [95% CI]	economic values/(million US$)[a] [95% CI]
mortality, all cause	376 [254–496]	329360 [30731–897675]
respiratory hospital admissions	128 [-35–231]	367 [4–590]
cardiovascular hospital admissions	111 [71–152]	435 [300–570]
chronic bronchitis	252 [7–491]	3051 [444–6665]
acute myocardial infarction, non-fatal	39 [19–60]	378 [181–566]
asthma emergency room visits	205 [-78–436]	9 [-2–19]
acute bronchitis	534 [-133–1157]	25 [-1–68]
asthma exacerbation	30630 [-616–61736]	173 [-5–436]
acute respiratory symptoms	281759 [230003–333283]	888 [44–1810]
total	/	334686 [31696–908399]

Note: a) the economic values include an inflation and income growth adjustment over time (2010 US$)

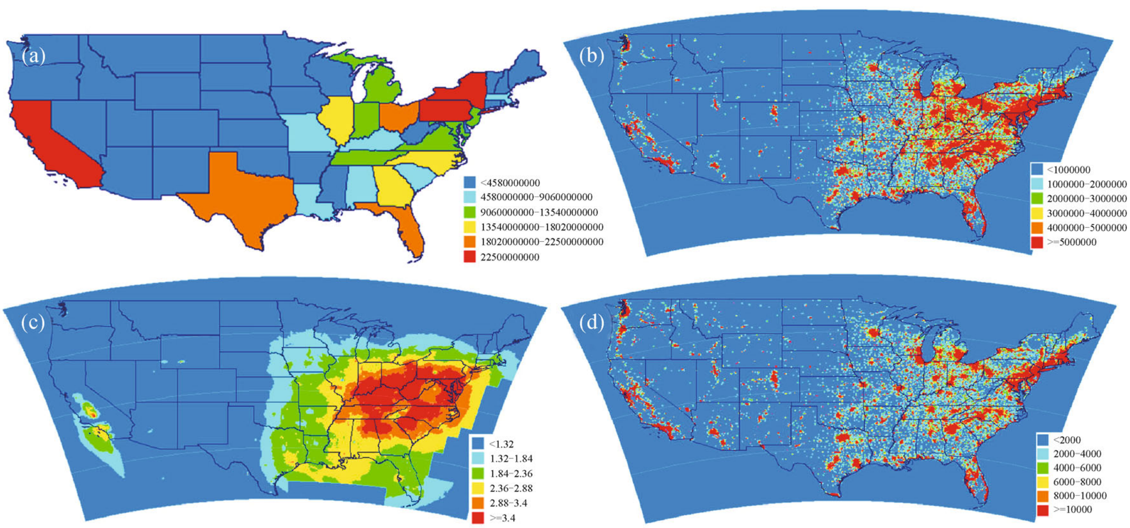

Fig. 5 Distribution of (a) aggregated total economic benefits in states (US$), (b) total economic benefits (US$), (c) air quality benefits ($\mu g \cdot m^{-3}$) and (d) population data of 0–99 age range (person) in 12 km × 12 km spatial resolution

both the targeted air quality and large increase in health and economic benefits. Besides, regions with high ratio (e.g., California, Texas) would suggest higher priority in the implementation of the control strategy.

Fann et al. [18] estimated the health and economic benefits of eliminating each ton of $PM_{2.5}$ and $PM_{2.5}$ precursor (SO_2 and NO_x) emission in the conterminous US in 2005 using the legacy BenMAP. Based on the presented total emissions (Fann et al. [18] Table1) and estimated benefit results of per-ton emission reduction (Fann et al. [18] Fig. 2), we manually calculated the economic benefits of the emission control scenario same to our case study. The independent benefits of direct $PM_{2.5}$, SO_2 and NO_x reduction were calculated first, and then added up to get the total economic benefits as US$373 billion. The final benefits result is in good agreement with the economic

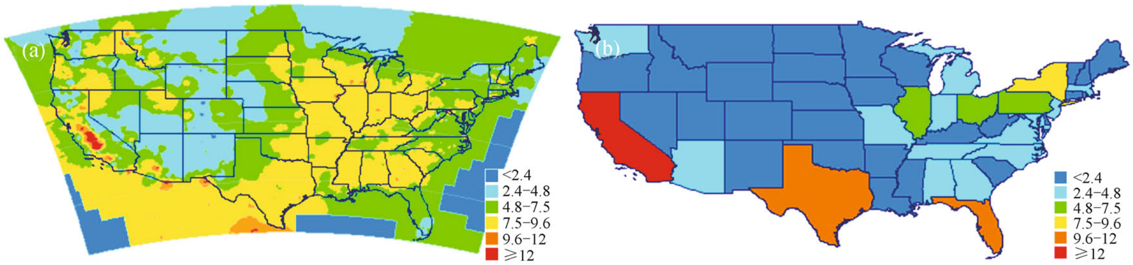

Fig. 6 Combining the predicted air quality in future year and the science-specific ratio of economic benefits to air quality benefits to improve the air pollution control strategy: (a) predicted concentration distribution of annual $PM_{2.5}$ in 2020 ($\mu g \cdot m^{-3}$); (b) distribution of the ratio of the economic benefits to air quality benefits in each state (billion US$ per $\mu g \cdot m^{-3}$)

benefits estimated in our study (US$334 billion). The deviation of the results is mainly caused by the difference of the studied health endpoints and analysis year: (1) the estimated results in Fann et al. [18] include additional benefits from reductions in work loss days, upper respiratory symptoms and lower respiratory symptoms; (2) the study year is 2005 in Fann et al. [18] and 2020 in our study, which indicates that the used incidence rates and the population data in these two analyses have a little difference. Nonetheless, the overall agreement between our results and those reported by Fann et al. [18] corroborates the reliability of the integrated assessment platform.

3.2 Advantages of integrated assessment platform

This software development based on SMAT-CE and BenMAP-CE offers multiple advantages in the assessment of air quality improvement and its economic benefits. First, the software eliminates the operational burden of data format conversion and input file preparation for BenMAP-CE. The newly developed linking module automates the conversion of point-based data to area-based data, creation of required data fields and intermediate data files (e.g., baseline and control), and retrieval of baseline and control data. Compared to the manual operation time of the above steps (the spatial join operation is based on ArcGIS tool), this new module reduces the operational burden by 43%. Secondly, it significantly decreases the runtime of interpolation process in SMAT-CE by 73% through the optimization of the computational algorithms for the presented US case study. Thirdly, users have an easy access to a suite of air quality management tools through a familiar Windows user interface. The developed software platform is presented in a user-friendly graphical interface and has standard windows-style operation. Finally, the integrated assessment platform of SMAT-CE and BenMAP-CE can provide comprehensive air quality and health and economic benefits to policy makers for formulating an effective and optimized air pollution control strategy.

Further improvement of the assessment platform will be extending the analysis of AQ-health benefit to cost-benefit, which can be achieved by integrating our developing software for air pollution control cost evaluation (Control Strategy Tool-Community Edition, CoST-CE) in the near future. The integrated cost-benefit analysis system can provide more intuitive information, such as how many monetary health benefits can be earned comparing to the control cost. Through balancing the engineering cost and human health benefits, policy makers can then get the cost-effective air pollution control strategy.

4 Conclusions

This paper describes an integration of SMAT-CE (Software for Model Attainment Test-Community Edition) and BenMAP-CE (Environmental Benefits Mapping and Analysis Program-Community Edition) for assessing air quality attainment and the health and economic benefits of emission control strategies. The developed platform assesses the effectiveness of a proposed emission reduction in meeting specified air quality standards, and seamlessly quantifies the corresponding monetary health benefits. The newly developed computational module significantly enhances the computational efficiency in the two stand-alone software packages and simplifies the data pre-processing with a friendly graphical user interface.

The case study demonstrates that the integrated assessment platform is capable of examining the attainment of the NAAQS by a proposed emission control strategy for $PM_{2.5}$ and analyzing the health and economic benefits. The software not only provides comprehensive information to support selecting appropriate air pollution control strategy, but also offers a science-specific ratio of health and economic benefits to air quality benefits for strategy optimization. The presented software serves as a comprehensive and efficient assessment platform for policy makers to evaluate air quality improvement as well as health and economic benefits of air pollution control.

Acknowledgements Financial support and data source for this work is provided by the US Environmental Protection Agency (Subcontract No. A14-0568-S001). This work is also partly supported by the funding of Guangdong

Provincial Key Laboratory of Atmospheric Environment and Pollution Control (No. 2011A060901011), the project of Atmospheric Haze Collaboration Control Technology Design (No. XDB05030400) from Chinese Academy of Sciences and the National Environmental Protection Public Welfare Industry Targeted Research Foundation of China (No. 201409019).

References

1. Beelen R, Raaschou-Nielsen O, Stafoggia M, Andersen Z J, Weinmayr G, Hoffmann B, Wolf K, Samoli E, Fischer P, Nieuwenhuijsen M, Vineis P, Xun W W, Katsouyanni K, Dimakopoulou K, Oudin A, Forsberg B, Modig L, Havulinna A S, Lanki T, Turunen A, Oftedal B, Nystad W, Nafstad P, de Faire U, Pedersen N L, Östenson C G, Fratiglioni L, Penell J, Korek M, Pershagen G, Eriksen K T, Overvad K, Ellermann T, Eeftens M, Peeters P H, Meliefste K, Wang M, Bueno-de-Mesquita B, Sugiri D, Krämer U, Heinrich J, de Hoogh K, Key T, Peters A, Hampel R, Concin H, Nagel G, Ineichen A, Schaffner E, Probst-Hensch N, Künzli N, Schindler C, Schikowski T, Adam M, Phuleria H, Vilier A, Clavel-Chapelon F, Declercq C, Grioni S, Krogh V, Tsai M Y, Ricceri F, Sacerdote C, Galassi C, Migliore E, Ranzi A, Cesaroni G, Badaloni C, Forastiere F, Tamayo I, Amiano P, Dorronsoro M, Katsoulis M, Trichopoulou A, Brunekreef B, Hoek G. Effects of long-term exposure to air pollution on natural-cause mortality: an analysis of 22 European cohorts within the multicentre ESCAPE project. Lancet, 2014, 383(9919): 785–795
2. Kan H, Wong C M, Vichit-Vadakan N, Qian Z. Short-term association between sulfur dioxide and daily mortality: the Public Health and Air Pollution in Asia (PAPA) study. Environmental Research, 2010, 110(3): 258–264
3. Wan Mahiyuddin W R, Sahani M, Aripin R, Latif M T, Thach T Q, Wong C M. Short-term effects of daily air pollution on mortality. Atmospheric Environment, 2013, 65(0): 69–79
4. Dockery D W, Stone P H. Cardiovascular risks from fine particulate air pollution. New England Journal of Medicine, 2007, 356(5): 511–513
5. Karakatsani A, Kapitsimadis F, Pipikou M, Chalbot M C, Kavouras I G, Orphanidou D, Papiris S, Katsouyanni K. Ambient air pollution and respiratory health effects in mail carriers. Environmental Research, 2010, 110(3): 278–285
6. Tao Y, Mi S, Zhou S, Wang S, Xie X. Air pollution and hospital admissions for respiratory diseases in Lanzhou, China. Environmental Pollution, 2014, 185(0): 196–201
7. World Health Organization. Burden of disease from Ambient Air Pollution for 2012. 2014. Available online at http://www.who.int/phe/health_topics/outdoorair/databases/AAP_BoD_results_-March2014.pdf?ua = 1 (accessed March 2014)
8. Naiker Y, Diab R D, Zunckel M, Hayes E T. Introduction of local Air Quality Management in South Africa: overview and challenges. Environmental Science & Policy, 2012, 17(0): 62–71
9. Ma G, Wang J, Yu F, Zhang Y, Cao D. An assessment of the potential health benefits of realizing the goals for PM_{10} in the updated Chinese Ambient Air Quality Standard. Frontiers of Environmental Science & Engineering, DOI: 10.1007/s11783-014-0738-x
10. Carnevale C, Finzi G, Pisoni E, Volta M, Guariso G, Gianfreda R, Maffeis G, Thunis P, White L, Triacchini G. An integrated assessment tool to define effective air quality policies at regional scale. Environmental Modelling & Software, 2012, 38(0): 306–315
11. Yang Y, Zhu Y, Jang C, Xie J P, Wang S X, Fu J, Lin C J, Ma J, Ding D, Qiu X Z, Lao Y W. Research and development of environmental benefits mapping and analysis program: community edition. Acta Scientiae Circumstantiae, 2013, 33(09): 2395–2401 (in Chinese)
12. Wang H, Zhu Y, Jang C, Lin C J, Wang S, Fu J S, Gao J, Deng S, Xie J, Ding D, Qiu X, Long S. Design and demonstration of a next-generation air quality attainment assessment system for $PM_{2.5}$ and O_3. Journal of Environmental Sciences (China), 2015, 29(0): 178–188
13. Lao Y W, Zhu Y, Carey J, Lin C J, Xing J, Chen Z R, Xie J P, Wang S X, Fu J. Research and development of regional air pollution control decision support tool based on response surface model. Acta Scientiae Circumstantiae, 2012, 32(8): 1913–1922 (in Chinese)
14. Sun J, Schreifels J, Wang J, Fu J S, Wang S. Cost estimate of multi-pollutant abatement from the power sector in the Yangtze River Delta region of China. Energy Policy, 2014, 69(0): 478–488
15. Microsoft. DotSpatial. 2013. Available online at http://dotspatial.codeplex.com/SourceControl/latest#Trunk/DotSpatial.Analysis/Voronoi.cs (accessed March, 2013)
16. Abt Associates Inc. Modeled Attainment Test Software User's Manual. 2014. Available online at http://www.epa.gov/ttn/scram/guidance/guide/MATS_2-6-1_manual.pdf (accessed April 2014)
17. U.S. EPA. Modeling Guidance for Demonstrating Attainment of Air Quality Goals for Ozone, $PM_{2.5}$, and Regional Haze. 2014. Available online at http://www.epa.gov/ttn/scram/guidance/guide/Draft_O3-PM-RH_Modeling_Guidance-2014.pdf (accessed December, 2014)
18. Fann N, Baker K R, Fulcher C M. Characterizing the $PM_{2.5}$-related health benefits of emission reductions for 17 industrial, area and mobile emission sectors across the U.S. Environment International, 2012, 49: 141–151
19. Davidson K, Hallberg A, McCubbin D, Hubbell B. Analysis of $PM_{2.5}$ using the Environmental Benefits Mapping and Analysis Program (BenMAP). Journal of Toxicology and Environmental Health-part A-current Issues, 2007, 70(3–4): 332–346
20. International R T I. Environmental Benefits Mapping and Analysis Program User's Manual Appendices. 2015. Available online at http://www2.epa.gov/sites/production/files/2015-04/documents/benmap-ce_user_manual_appendices_march_2015.pdf (accessed March 2015)
21. International R T I. Environmental Benefits Mapping and Analysis Program User's Manual. 2015. Available online at http://www2.epa.gov/sites/production/files/2015-04/documents/benmap-ce_user_-manual_march_2015.pdf (accessed March 2015)
22. Krewski D, Jerrett M, Burnett R T, Ma R, Hughes E, Shi Y, Turner M C, Pope C A 3rd, Thurston G, Calle E E, Thun M J, Beckerman B, DeLuca P, Finkelstein N, Ito K, Moore D K, Newbold K B, Ramsay T, Ross Z, Shin H, Tempalski B. Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality. Research Report (Health Effects Institute), 2009, 140(140): 5–114, discussion 115–136
23. Woodruff T J, Grillo J, Schoendorf K C. The relationship between

selected causes of postneonatal infant mortality and particulate air pollution in the United States. Environmental Health Perspectives, 1997, 105(6): 608–612

24. Woodruff T J, Parker J D, Schoendorf K C. Fine particulate matter ($PM_{2.5}$) air pollution and selected causes of postneonatal infant mortality in California. Environmental Health Perspectives, 2006, 114(5): 786–790
25. Zanobetti A, Franklin M, Koutrakis P, Schwartz J. Fine particulate air pollution and its components in association with cause-specific emergency admissions. Environmental Health, 2009, 8(1): 58
26. Kloog I, Coull B A, Zanobetti A, Koutrakis P, Schwartz J D. Acute and chronic effects of particles on hospital admissions in New-England. PLoS ONE, 2012, 7(4): e34664
27. Moolgavkar S H. Air pollution and hospital admissions for chronic obstructive pulmonary disease in three metropolitan areas in the United States. Inhalation Toxicology, 2000, 12(Suppl 4): 75–90
28. Babin S M, Burkom H S, Holtry R S, Tabernero N R, Stokes L D, Davies-Cole J O, DeHaan K, Lee D H. Pediatric patient asthma-related emergency department visits and admissions in Washington, DC, from 2001-2004, and associations with air quality, socio-economic status and age group. Environmental Health, 2007, 6(1): 9
29. Bell M L, Ebisu K, Peng R D, Walker J, Samet J M, Zeger S L, Dominici F. Seasonal and regional short-term effects of fine particles on hospital admissions in 202 US counties, 1999–2005. American Journal of Epidemiology, 2008, 168(11): 1301–1310
30. Bell M L. Assessment of the health impacts of particulate matter characteristics. Research Report (Health Effects Institute), 2012, 161(161): 5–38
31. Moolgavkar S H. Air pollution and hospital admissions for diseases of the circulatory system in three U.S. metropolitan areas. Journal of the Air & Waste Management Association, 2000, 50(7): 1199–1206
32. Abbey D E, Ostro B E, Petersen F, Burchette R J. Chronic respiratory symptoms associated with estimated long-term ambient concentrations of fine particulates less than 2.5 microns in aerodynamic diameter ($PM_{2.5}$) and other air pollutants. Journal of Exposure Analysis and Environmental Epidemiology, 1995, 5(2): 137–159
33. Slaughter J C, Kim E, Sheppard L, Sullivan J H, Larson T V, Claiborn C. Association between particulate matter and emergency room visits, hospital admissions and mortality in Spokane, Washington. Journal of Exposure Analysis and Environmental Epidemiology, 2005, 15(2): 153–159
34. Mar T F, Koenig J Q, Primomo J. Associations between asthma emergency visits and particulate matter sources, including diesel emissions from stationary generators in Tacoma, Washington. Inhalation Toxicology, 2010, 22(6): 445–448
35. Glad J A, Brink L L, Talbott E O, Lee P C, Xu X, Saul M, Rager J. The relationship of ambient ozone and $PM_{2.5}$ levels and asthma emergency department visits: possible influence of gender and ethnicity. Archives of Environmental & Occupational Health, 2012, 67(2): 103–108
36. Dockery D W, Cunningham J, Damokosh A I, Neas L M, Spengler J D, Koutrakis P, Ware J H, Raizenne M, Speizer F E. Health effects of acid aerosols on North American children: respiratory symptoms. Environmental Health Perspectives, 1996, 104(5): 500–505
37. Ostro B, Lipsett M, Mann J, Braxton-Owens H, White M. Air pollution and exacerbation of asthma in African-American children in Los Angeles. Epidemiology (Cambridge, Mass), 2001, 12(2): 200–208
38. Ostro B D, Rothschild S. Air pollution and acute respiratory morbidity: an observational study of multiple pollutants. Environmental Research, 1989, 50(2): 238–247