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Evaluation of health benefit using BenMAP-CE with an integrated scheme of model and monitor data during Guangzhou Asian Games

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ABSTRACT

Guangzhou is the capital and largest city (land area: 7287 km^2) of Guangdong province in South China. The air quality in Guangzhou typically worsens in November due to unfavorable meteorological conditions for pollutant dispersion. During the Guangzhou Asian Games in November 2010, the Guangzhou government carried out a number of emission control measures that significantly improved the air quality. In this paper, we estimated the acute health outcome changes related to the air quality improvement during the 2010 Guangzhou Asian Games using a next-generation, fully-integrated assessment system for air quality and health benefits. This advanced system generates air quality data by fusing model and monitoring data instead of using monitoring data alone, which provides more reliable results. The air quality estimates retain the spatial distribution of model results while calibrating the value with observations. The results show that the mean $PM_{2.5}$ concentration in November 2010 decreased by 3.5 μg/m^3 compared to that in 2009 due to the emission control measures. From the analysis, we estimate that the air quality improvement avoided 106 premature deaths, 1869 cases of hospital admission, and 20,026 cases of outpatient visits. The overall cost benefit of the improved air quality is estimated to be 165 million CNY, with the avoided premature death contributing 90% of this figure. The research demonstrates that BenMAP-CE is capable of assessing the health and cost benefits of air pollution control for sound policy making.

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Introduction

Along with the rapidly booming economy and urbanization, the Pearl River Delta (PRD, including Guangzhou, Shenzhen, *etc.*) region has been suffering from serious PM (particulate matter) and ozone air pollution in recent years (Wu et al., 2007, 2012a). The PM pollution in the PRD region is worse in autumn and winter due to the unfavorable meteorological conditions for pollutant dispersion. With the goal of attaining better air quality (air pollution index ≤ 100) during the 16th Guangzhou Asian Games in November 2010, about 2.4 billion Chinese Yuan (CNY) was invested to implement a number of air pollution control measures in Guangzhou since 2008, including industrial emission reduction, traffic restriction, fugitive dust control, *etc.*, in Guangzhou and surrounding cities (including Foshan, Dongguan, *etc.*). The observed air quality improved significantly in November 2010 compared to in 2009 although the dispersion conditions were worse than in 2009 (Wu et al., 2012b). However, the health and cost benefits of the improved air quality remained unclear.

Health impacts and benefits associated with air quality improvements have been studied previously. The US Environmental Protection Agency (US EPA, 1999), World Bank (World Bank, 2007), and WHO (Cohen et al., 2005) quantified the health effects of air pollution. Hong Kong University (Civic Exchange, 2008) estimated that nearly 10,000 deaths in the Southern China region in 2006, with the majority (94%) occurring in the PRD, were due to air pollution. Huang and Zhang (2013) evaluated the health benefits for the Jingjinji area assuming the attainment of a new national ambient air quality standard (GB3095-2012). Kan and Chen (2004); Yuan and Dong (2006) and Zhang et al. (2007, 2008) estimated the health impact and economic loss due to the particulate matter pollution of China cities. Hou et al. (2011) calculated the health-related economic loss due to PM_{10} in Lanzhou during 2002–2009. Hou et al. (2010) analyzed human exposure to PM_{10} and associated economics during the Beijing Olympic Games. Gao et al. (2015) assessed the health impacts and economic losses of the 2013 severe smog event in Beijing. There are increasing studies on health impact assessment in China, but none of these works use both model and monitoring data through use of an interpolation method to perform the analysis.

In this study, the US EPA's next-generation integrated air quality attainment and evaluation system were applied to evaluate the benefits to public health due to air quality improvement during the Guangzhou Asian Games. This integrated assessment system includes and links two modules: (1) the Software for Model Attainment Test-Community Edition (SMAT-CE, available at http://www.abacas-dss.com/), which can predict the baseline/future year air quality with model simulation data and observation data (Wang et al., 2015), and (2) the environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE, available at http://www.epa.gov/airquality/benmap/ce.html), which is an integrated geographic information system (GIS) tool capable of estimating the health impacts and associated economic benefits resulting from changes in air quality (Yang et al., 2013). SMAT-CE provides air quality data for BenMAP-CE as input. This data transmission can be automatically realized in the assessment system after clicking the "Link to BenMAP" button in SMAT-CE. To improve the accuracy of the air quality and evaluation results, SMAT-China (China version of SMAT-CE) was applied to generate the model and related monitor air quality grid data (combining model and monitoring data by using an interpolation method) as the input for BenMAP-CE. The integrated assessment system can fill the gaps in previous works from simply using modeled/monitoring air quality values to assess health benefits. Here we present the approach and provide estimates of health benefits due to air quality improvement in November 2009 and November 2010 in Guangzhou.

1. Methodology

1.1. *Health benefit evaluation method*

Fig. 1 describes the analytical steps. $PM_{2.5}$ (particulate matter with a size ≤ 2.5 μm) was chosen as the air pollution indicator. The EPA's Community Multiscale Air Quality (CMAQ) model was applied to simulate the $PM_{2.5}$ baseline and control concentration of Guangzhou. SMAT-China was utilized to generate the modeled and related monitor values as the input for BenMAP-CE. Then BenMAP-CE was applied to estimate human health effects and benefits resulting from changes in air quality, with the input data including population, incidence rates, and unit value for health endpoints.

In SMAT-China, an algorithm for Voronoi neighbor averaging (VNA) was adopted to interpolate air quality monitoring data to obtain the air quality data at unmonitored locations (US EPA, 2007; Wang et al., 2015). Neighboring monitors were identified by drawing a Voronoi diagram using the centroid of the grid cell and all monitors, then we calculated an inverse-distance (or square inverse-distance) weighted average of the neighboring monitors as the grid value. The equation is shown below:

$$\text{GridCell}_E = \sum_{i=1}^{n} \text{Weight}_i \times \text{Monitor}_i \tag{1}$$

where n is the number of neighboring sites, Weight_i is the inverse distance weight for monitor i, Monitor_i is the observed data at monitor i, and GridCell_E is the value at grid cell E.

Another interpolation method used model data to adjust the VNA spatial field results (eVNA), by multiplying the ratio of the model value in the unmonitored area with the model value at the grid cell containing the monitor:

$$\text{GridCell}_E = \sum_{i=1}^{n} \text{Weight}_i \times \text{Monitor}_i \times \frac{\text{Model}_E}{\text{Model}_i} \tag{2}$$

where Model_E is the model data at cell E, and Model_i is the model data at the grid cell which contains monitor site i. This approach takes the monitor and model value into account since the monitor value provides the real observed concentration, while the model value can provide the spatial distribution of $PM_{2.5}$ concentration in addition. In this case, eVNA was applied to generate air quality input data for BenMAP-CE. The detailed comparison is discussed in Section 2.1.1.

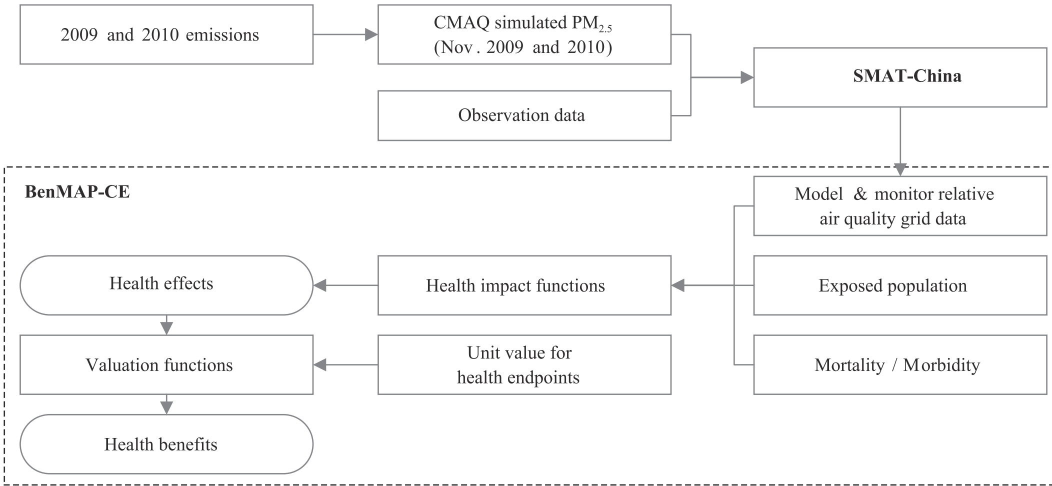

Fig. 1 – Conceptual diagram of steps in health benefit calculation. SMAT: the Software for Model Attainment Test; CMAQ: Community Multiscale Air Quality; BenMAP-CE: the environmental Benefits Mapping and Analysis Program—Community Edition.

BenMAP-CE v1.0.8 was applied to evaluate the health impacts and economic benefit of the air improvement. BenMAP-CE (US EPA, 2012) needs three steps to perform an analysis: 1. create an air quality surface; 2. estimate health impact; 3. monetize health benefit. The air quality delta surface was created by the baseline and control air quality generated by SMAT-China. Concentration–response functions (CRFs) were used to calculate the health incidence results due to PM concentration change in BenMAP-CE. This method has been widely used in domestic and international research for quantifying health risks (Fann et al., 2013; Voorhees et al., 2011). Air pollution and health endpoints are linked in a relative risk model in most of the epidemiologic studies, while a log-linear CRF can be derived as shown below (Fann et al., 2009):

$$\Delta Y = Y_0\left(1{-}e^{-\beta\Delta PM}\right) \times \text{Pop} \tag{3}$$

where Pop is the exposed population, the dimensionless coefficient β is derived from relative risk reported in the epidemiological reference, and ΔPM is the air quality change in the control year (after implementing control measures, 2010 in this case) compared to the baseline year (before implementing control measures, 2009 in this case), Y_0 is the incidence rate in the baseline year, ΔY is the attributable number of cases which equals the difference in corresponding health effects under the baseline year and control year. If these data components including the baseline incidence of health endpoints (Y_0), the coefficients of exposure–response functions (β), and the change of air pollutant concentration (ΔPM) are obtained, the reduced health impact attributable to the improved air quality can be estimated. BenMAP-CE utilizes a Monte Carlo approach and specifies Latin hypercube points to estimate the health effects of generating specified percentiles along with the distribution of β. BenMAP-CE would generate the 0.5th, 1.5th, 2.5th… and 99.5th points when using 100 Latin Hypercube points. The Latin hypercube points were used for presenting confidence intervals (CI) for health impact analysis.

Monetized health effects provide direct and quantified economic benefits to policy-makers for evaluating air pollution control strategies. Three monetization methods including willingness to pay (WTP), cost of illness (COI), and human capital (HC) approach are commonly used in valuating environmental health (World Health Organization, 2009). The WTP approach comprehensively measures the amount of money people are willing to pay for the reduction in the risk of illness. The COI approach is used to measure the cost of health endpoints, including medical resources used and the value of lost productivity. The HC approach measures the lost production due to illness by multiplying the period of absence by the wage rate of the absent worker. In general, WTP is the most widely preferred used method because it takes intangible losses into account, such as pain, suffering and other adverse effects due to illness (Robinson, 2011). Using the unit value for each health endpoint, the reduced health impact can be monetized to the health benefit by Eq. (4) as follows:

$$M = \sum \Delta Y_i \times V_i \tag{4}$$

where ΔY_i is the impact for health endpoint i, V_i is the unit economic value of health endpoint i, and M is the sum of economic change of health endpoints.

1.2. Input data

1.2.1. $PM_{2.5}$ concentration

Model data and observation data were both used in the study. Model data for the $PM_{2.5}$ concentration in Guangzhou were simulated by CMAQ v4.7.1 with the spatial resolution of 3 × 3 km. The basic emission inventory (for 2009, spatial resolution: 3 × 3 km) was obtained from the Guangzhou Asian Games air quality assessment program by Tsinghua University. The emission inventory contains six pollutants, *i.e.*, SO_2, NO_x, CO, PM_{10}, $PM_{2.5}$, and volatile organic compounds (VOC). The major categories are power plants, industry, mobile sources, area sources, VOC-related sources, biogenic sources and others. The control scenario (2010) was assessed using the emission reduction due to the control measures based on the baseline scenario. The following series of measures were implemented to improve air quality: restructuring of the power plant and industry boilers to reduce emissions of sulfur and nitrogen oxides to the atmosphere; reduction of exhaust emissions by closing the area to traffic except for green label cars and implementing the odd-and-even license plate rule (*e.g.*, vehicles with even registration numbers are only allowed on-road in even-number dates); reduction of the road and construction fugitive dust by sprinkling water on the roads and stopping construction; reduction of VOC-related sources by gas recovery at petrol stations, adopting effective VOC emission controls in key industries, and promoting the use of low-VOC emission paint and paint products. The percentage reductions of SO_2, NO_x, CO, PM_{10}, $PM_{2.5}$, and VOC emissions in different sources (Table 1) were obtained from the final official technical report, which were calculated according to the control measures mentioned in the report of the Guangzhou air pollution control office.

Daily PM observation data for November, 2009 and 2010 were obtained from the Guangzhou Environmental Monitoring Center. For the sites that had PM_{10} data only, $PM_{2.5}$ was calculated as 70% of the PM_{10} level (Liu et al., 2010). Fig. 2 shows the observational sites in Guangzhou. There are 18 monitoring stations, 10 of which are national air quality monitoring sites.

1.2.2. *Exposed population*

BenMAP-CE can assess the health impact for different groups classified by age range, gender, race and ethnicity. In this study, the total population was used to represent the exposed population without classification by age or gender due to the lack of available population data. According to the Guangzhou statistics yearbook (2011) (Statistics Bureau of Guangdong Province, 2011) and the sixth national population census data communiqué, the total population in Guangzhou in 2010 was 12.7 million. The population distribution of each administration district is shown in Fig. 3. BenMAP-CE can generate population data to different grid definition levels (such as 12 km, city, *etc.*) based on the original data through a spatially-weighted average approach.

1.2.3. *Selection of CRFs and mortality/morbidity rates*

CRF is the key factor to quantitatively evaluate the health impact caused by air pollution. The health endpoints were selected based on the literature (World Bank, 2007): (1) those

Table 1 – Pollutant emission reduction (%) during Guangzhou Asian Games compared to 2009.

Sources	SO_2	NO_x	CO	PM_{10}	$PM_{2.5}$	VOC
Power plant	35.9	56.6	–	–	–	–
Industry	14.1	20.6	4.7	6.0	7.9	16.9
On-road mobile sources	47.2	41.2	60.0	36.2	36.2	52.0
Non-road mobile sources	22.3	13.0	3.2	8.8	8.6	–
Fugitive dust	–	–	–	62.4	62.4	–
VOC product-related	–	–	–	–	–	75.7

VOC: volatile organic compounds.
–: without control.

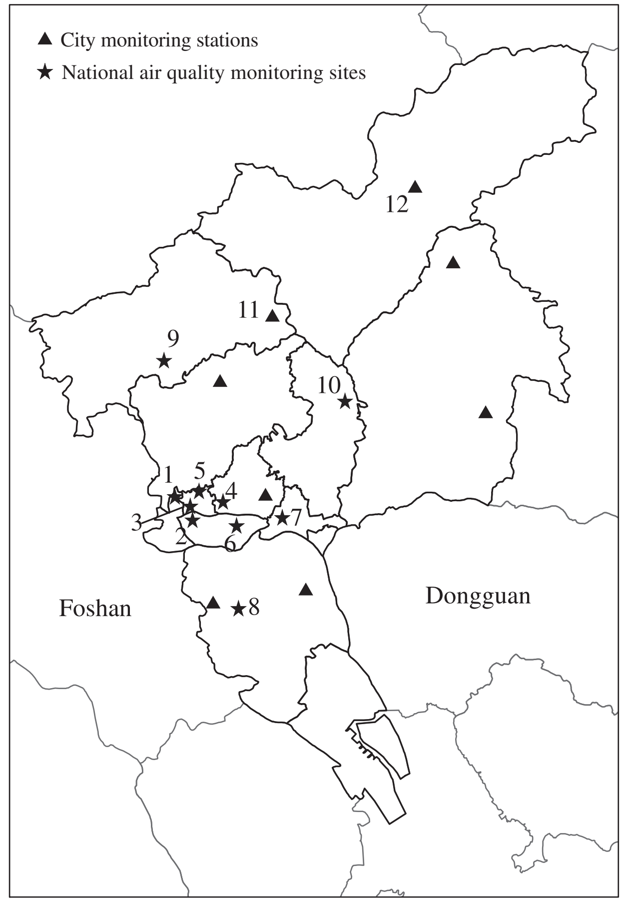

Fig. 2 – District map of Guangzhou with locations of city monitoring stations and national air quality monitoring sites.

registered in Chinese cities and classified by ICD-10 (International Classification of Diseases) code; (2) those published in exposure–response studies; and (3) statistical data such as mortality/morbidity incidence rates. Accordingly, the health endpoints of all-cause mortality, all-cause hospital admissions, all-cause outpatient visits, mortality for respiratory and cardiovascular disease, and hospital admissions for respiratory and cardiovascular disease were selected. In this case, those CRFs (Table 2) reported in epidemiological studies of acute health effects were chosen to assess health impact. The CRFs applied for 0–99 age ranges were selected since the population in different age ranges was unavailable. Several studies assessed the exposure to particulate matter of different diameters such as PM_{10} and total suspended particulate (TSP), so conversion factors (0.65 for PM_{10} to TSP, 0.7 for $PM_{2.5}$ to PM_{10}) were applied (Kan and Chen, 2004; Liu et al., 2010) if necessary. The CRFs under the same health endpoint were combined using a fixed-effects pooling procedure. Each estimate was weighted in proportion to the inverse of the variance. Table 3 shows the annual baseline incidence rates for each chosen health endpoint. The annual incidence rates (in 2009) were obtained from the China statistics yearbook (2010) (National Bureau of Statistics of China, 2010) and China health statistics yearbook (2010) (National Health and Family Planning Commission of China, 2010).

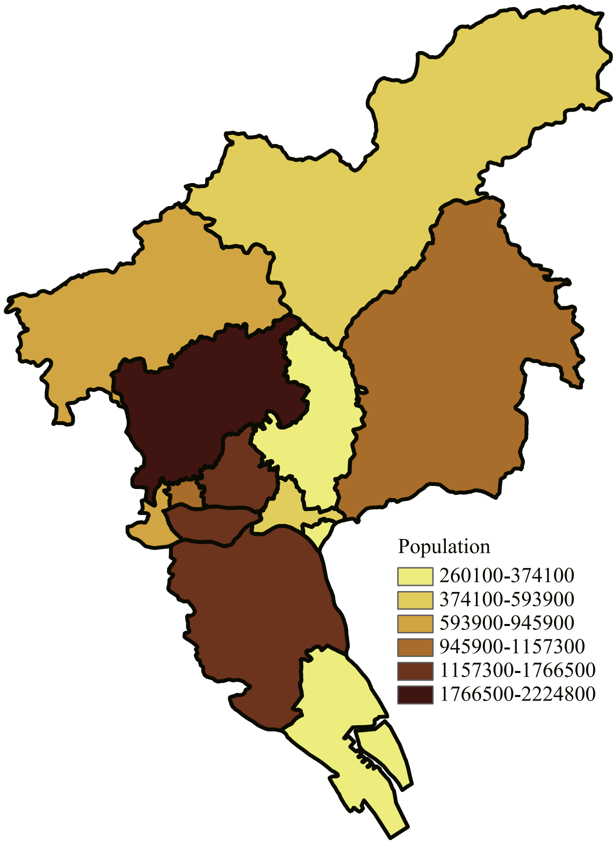

Fig. 3 – Population of Guangzhou administration district (2010).

1.2.4. Selection of monetization method

Table 4 shows the unit values for economic valuation of various health endpoints. The WTP value is associated with human income and will be different for regions with different economic status. In this case, the unit value for Guangzhou was generated from the original value for studies in reported

Table 3 – Baseline incidence rates for included mortality and morbidity endpoints.

Health endpoints	Baseline incidence ($\times 10^{-3}$/year)
Mortality, all cause	4.52
Mortality, respiratory	0.64
Mortality, cardiovascular	1.30
Hospital admissions, all cause	62.27
Hospital admissions, cardiovascular	11.30
Hospital admissions, respiratory	7.80
Outpatient visits, all cause	2411.19

cities (Chongqing/Beijing) multiplied by the annual capita income ratio between Guangzhou and the source city (Huang et al., 2012). Then the unit value for various currency years was adjusted to the year 2010 by multiplying by the annual consumer price index (CPI) in China (Voorhees et al., 2014). For hospital admission and outpatient visits, the COI and HC valuation approaches were applied. COI estimates the direct cost of a health outcome while HC measures the lost production. Both valuation estimates were updated to currency year 2010 using similar adjustments. Multiple valuation results under each endpoint were combined using average weights.

2. Results and discussion

2.1. Air quality data

2.1.1. Improvement in data preprocess

The interpolation method of eVNA was utilized to generate the air quality grid data for BenMAP-CE. Here we present the comparison of VNA and eVNA using the air quality data in 2009. Fig. 4a displays the average $PM_{2.5}$ concentration of CMAQ results for November, 2009. It is in good agreement with the spatial distribution of the road network and industries. Fig. 4b displays the air quality grid value interpolated from

Table 2 – Summary of the main features of the selected concentration–response functions (CRFs).

Health endpoints	Pollutant	References	Coefficient β	Location
Mortality, all cause	$PM_{2.5}$	Kan et al. (2007)	0.0036 (0.0011,0.0061)	Shanghai
	$PM_{2.5}$	Xie et al. (2009)	0.0040 (0.0019,0.0062)	Shanghai, Chongqing
	PM_{10}	Chen et al. (2012)	0.0035 (0.0018,0.0052)	16 Chinese cities
Mortality, respiratory	$PM_{2.5}$	Kan et al. (2007)	0.0095 (0.0016,0.0173)	Shanghai
	$PM_{2.5}$	Xie et al. (2009)	0.0143 (0.0085,0.0201)	Shanghai
	PM_{10}	Chen et al. (2012)	0.0056 (0.0031,0.0081)	16 Chinese cities
Mortality, cardiovascular	$PM_{2.5}$	Kan et al. (2007)	0.0041 (0.0001,0.0082)	Shanghai
	$PM_{2.5}$	Xie et al. (2009)	0.0053 (0.0015,0.0090)	Shanghai
	PM_{10}	Chen et al. (2012)	0.0044 (0.0023,0.0064)	16 Chinese cities
Hospital admissions, all cause	TSP	Chen (2004)	0.0026 (0.0006,0.0046)	Guangzhou
Hospital admissions, cardiovascular	PM_{10}	Wong et al. (2002)	0.0070 (0.0031,0.0109)	Hong Kong
	TSP	Chen (2004)	0.0029 (0.0001,0.0060)	Guangzhou
	PM_{10}	Xie et al. (2009)	0.0066 (0.0036,0.0095)	Hong Kong
Hospital admissions, respiratory	TSP	Chen (2004)	0.0034 (0.0004,0.0065)	Guangzhou
	PM_{10}	Xie et al. (2009)	0.0124 (0.0086,0.0162)	Hong Kong
Outpatient visits, all cause	PM_{10}	Cao et al. (2009)	0.0011 (−0.0003,0.0026)	Shanghai

Coefficient β represents the increase in acute health impact per 10 μg/m^3 increase of particulate matter pollution. Values in parentheses are 95% confidence interval (CI).
TSP: total suspended particulate.

Table 4 – Unit values for various health endpoints.

Health endpoints	Unit value (CNY)	Approach	References
Mortality	965041.7 (928614.8, 1001469.7)	WTP in 2010 CNY	Wang and Mullahy (2006)
	1709300 [a]	WTP in 2010 CNY	Mu and Zhang (2013)
Hospital admissions, all cause	7534 [a]	COI in 2010 CNY	National Health and Family Planning Commission of China (2011)
Hospital admissions, cardiovascular	6442 [a]	HC in 2010 CNY	Wan et al. (2005)
	5433 [a]	COI in 2010 CNY	Kan and Chen (2004)
	5006 [a]	COI in 2010 CNY	Zhang et al. (2008)
Hospital admissions, respiratory	3625 [a]	HC in 2010 CNY	Wan et al. (2005)
	3698 [a]	COI in 2010 CNY	Kan and Chen (2004)
	2454 [a]	COI in 2010 CNY	Zhang et al. (2008)
Outpatient visits, all cause	64 [a]	HC in 2010 CNY	Wan et al. (2005)
	106 [a]	COI in 2010 CNY	Xu and Jin (2003)

[a] The available data did not provide the distribution of the values. WTP: willingness to pay; COI: cost of illness; HC: human capital approach.

observation data only. The model value and the grid observed data show a largely consistent spatial distribution of concentration which increased from the northeast to the southwest of Guangzhou. However, model data provide a much more reasonable concentration distribution. Combining the advantages of model and observed data, air quality interpolated by using eVNA (Fig. 4c) can provide more accurate information that calibrates the value with observations while retaining the spatial distribution of model results. The leave-one-out validation method was used to verify the accuracy of VNA and eVNA. Air quality grid data were generated by both interpolation methods after removing one site each time, then compared with the observed value of the removed one. Table 5 displays the result of four observed sites as representative. No. 2 and No. 4 sites (Fig. 2) have the same bias for both VNA and eVNA because they are in the southwest of Guangzhou with high density of monitors around, while No. 11 and No. 12 sites show a larger bias for VNA because of the sparse interpolation sites.

2.1.2. $PM_{2.5}$ reduction

Baseline and control air quality data were generated by SMAT-China using the eVNA interpolation method with model and monitor data input. The CMAQ model data of November in 2009 and 2010 were compared to the observations at those grid cells that contained monitoring sites. The model results in both years slightly overestimate the average $PM_{2.5}$ observations (mean bias as 2.9 μg/m^3 for 2009 and 3.4 μg/m^3 for 2010). Fig. 5 shows a comparison between the simulated and observed daily $PM_{2.5}$ concentrations at the ten national air quality monitoring sites (Fig. 2) in Guangzhou. The comparison shows that model data were able to capture the temporal variation of observations, with the correlation coefficient ranging from 0.55 to 0.74 in 2009, and from 0.43 to 0.67 in 2010. The emission control measures during the Guangzhou Asian Games are the likely causes for the model over-prediction. By using the eVNA method, baseline/control $PM_{2.5}$ grid data were generated by combining monitoring data and observations. The air quality change was calculated from the interpolated baseline and control data. Fig. 6a shows the $PM_{2.5}$ concentration reduction in Guangzhou. According to the research of Wu et al. (2012b), the significant air pollution reduction was attributed to the effective transportation restrictions and industrial emission controls, because diffusion conditions were worse during the Guangzhou Asian

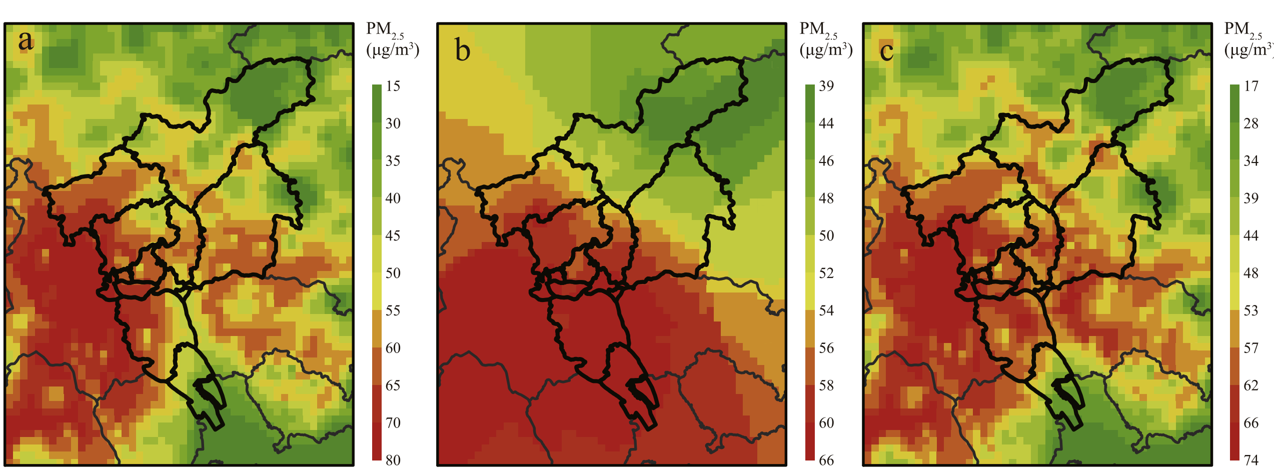

Fig. 4 – (a) Model data, (b) spatial field interpolated by using Voronoi neighbor averaging (VNA) and (c) spatial field interpolated by using model data to adjust the VNA spatial field results (eVNA).

Table 5 – Voronoi neighbor averaging (VNA) and model data to adjust the VNA spatial field results (eVNA) result comparison.

Monitor site	Normalized bias of VNA (%)	Normalized bias of eVNA (%)
Urban area		
No. 2	1.43	1.25
No. 4	1.99	1.92
Suburb area		
No. 11	15.66	4.99
No. 12	36.72	6.26

Games when compared to the same period of historical data. Tao et al. (2015) also found that air quality during the Asian Games period was much better than that observed in the same period without control measures in Guangzhou. Fig. 6b and c shows the distribution of the road network and industrial point sources in Guangzhou. Their intensity is very high in the urban area. Therefore, there were more emission reductions for on-road mobile, industry, and fugitive dust sources in the urban area than in the suburban area. Chen et al. (2010) indicated that air pollutants in Guangzhou mainly came from local emissions, and Dongguan and Foshan contributed most to Guangzhou of all the surrounding cities. The north suburban area of Guangzhou (Conghua) had a slightly lower concentration because it had better air quality compared to the urban area and was not the key area in the air pollution control strategy. Influenced by the wind from the northeast, air pollutant emission from Dongguan had an impact on air quality of south Guangzhou. Although Foshan is located in the downwind area of Guangzhou, it also affected the air quality in Guangzhou under a constantly changing wind direction because of its large amount of emission. The $PM_{2.5}$ reduction in the south of Guangzhou (Panyu, *etc.*) was low since it was associated with the intense emissions in the adjacent cities.

2.2. Health impact and valuation results

Table 6 lists the result of avoided acute health effects and the associated costs avoided from reduced morbidity and avoided premature deaths from the emission reduction during the 2010 Asian Games. According to the estimates, the average $PM_{2.5}$ observation value decreased 3.5 μg/m^3 and the public health benefit estimate was 165 million CNY. The benefits from three all-cause endpoints (mortality, hospital admissions, outpatient visits) are summed up as the total health benefits from air quality improvement.

The major health benefit was from the reduction in premature deaths, which contributed to 90% of the total cost. $PM_{2.5}$ pollution is most likely to cause cardiovascular and respiratory disease (Chapman et al., 1997; Linares and Díaz, 2010). The avoided death and illness due to cardiovascular or respiratory disease contributed to 73% and 61% of the total avoidable death and illness.

The distribution of health impact and benefit results of each health endpoint shows a similar spatial pattern. Fig. 7 depicts avoidable all-cause premature deaths for each grid cell and their saved economic costs (aggregated to county). It is estimated that the Baiyun district had the largest economic benefit, at 40 million CNY, because it has the highest population (Fig. 3) and greater air quality improvements in terms of PM2.5 concentration. This indicates that control strategies can result in higher benefits through focusing on the areas which have a high density of population with priority.

The reported research on chronic health impact in China is very sparse, especially that caused by $PM_{2.5}$. Kan and Chen (2002) distinguished between acute and chronic mortality for the effects of TSP. To avoid error from using data from different studies, Kan and Chen's results were used in an attempt to calculate the long-term and short-term mortality reductions and benefits of air improvement during the Guangzhou Asian Games. Results show that the economic benefit in terms of chronic mortality is 568.01 (95% CI, 181.94–

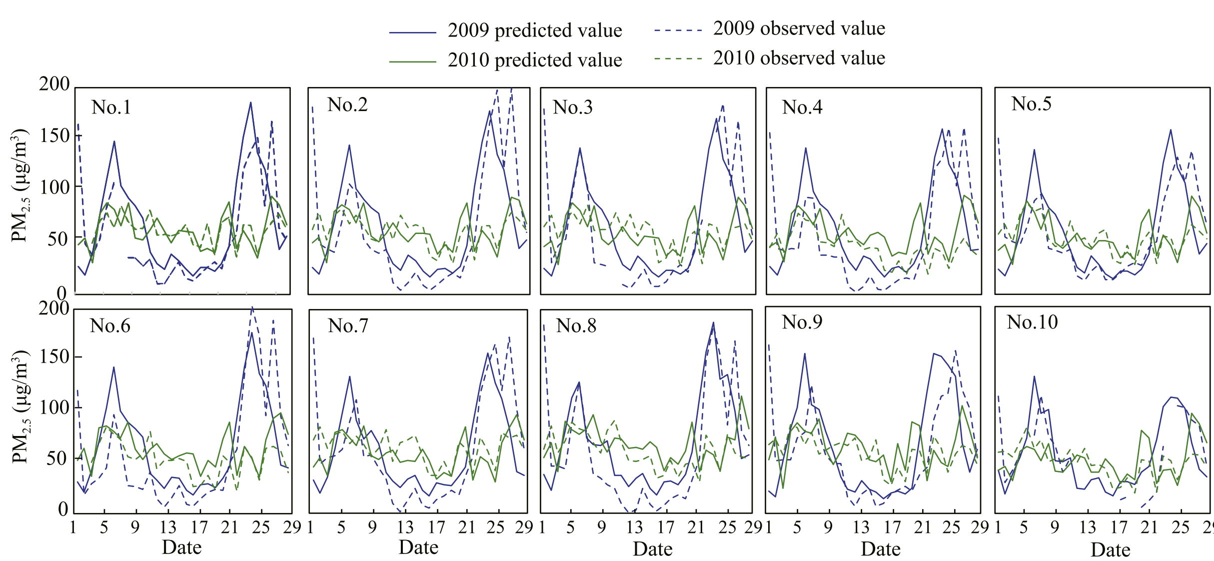

Fig. 5 – $PM_{2.5}$ observed and predicted pairs at national air quality monitoring sites for November 2009 and November 2010.

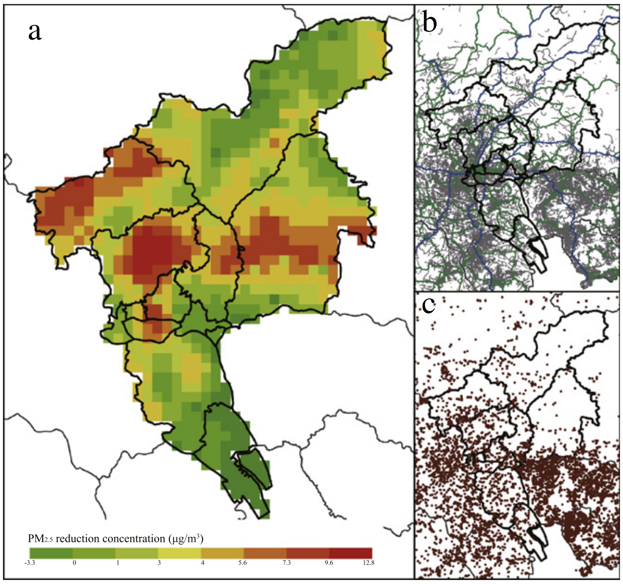

Fig. 6 – (a) Monthly $PM_{2.5}$ reduction in Guangzhou, (b) road distribution network map including national, provincial and city roads, and (c) industrial point source distribution in Guangzhou and surrounding area.

1179.81) million CNY, while the benefit to acute mortality is 175.65 (95% CI, 56.24–365.61) million CNY. The results show that the economic benefit for chronic mortality is larger than that for acute mortality. However, the current measures were taken to reduce fairly high concentrations in the short term. As the control measures were implemented during the Guangzhou Asian Games, the effect of air quality improvement only lasted one month, which produced less in terms of chronic health effect. To achieve long-term air quality improvement, fundamental and sustainable measures should be taken, such as energy structure reconstruction, industry emission control, development of public transportation, *etc.*

Table 6 – $PM_{2.5}$ reduction related health effects and benefits.

Health endpoints	Attributable number of cases per year	Benefit ($\times 10^6$ CNY/year)
Mortality, all cause	106 (44,162)	150 (59,277)
Mortality, cardiovascular	44 (15,79)	53 (17,106)
Mortality, respiratory	33 (15, 60)	46 (18,102)
Hospital admissions, all cause	1869 (402,3326)	14 (3,25)
Hospital admissions, cardiovascular	575 (311,838)	3.2 (1.7,5.1)
Hospital admissions, respiratory	565 (113,948)	1.8 (0.4,3.4)
Outpatient visits, all cause	20026 (−6540,46448)	1.7 (−0.6,4.6)
Total [a]		165 (62, 306)

Values in parentheses are 95% confidence interval (CI).
[a] Total = mortality, all cause + hospital admissions, all cause + outpatient visits, all cause.

2.3. Error analysis

The input data of this case study included air quality data, exposed population, CRFs, mortality/morbidity incidence rates, and monetary valuation functions. Each of these input data can affect the final results to different extents. The accuracy of results is interpreted cautiously in the following discussion.

Population and mortality/morbidity incidence rates were obtained from reliable data sources—the national/local statistics institute. The validity of health impact results depends basically on the selection of CRFs. There are relatively few quantitative studies on the relationship between air pollution, especially $PM_{2.5}$, and health impact for Chinese cities, compared with the foreign literature. Compared to the United States, China's health impact coefficient is much lower. A recent study reported by the California Air Resources Board (2008) indicates that the risk of death rises as much as 10% per 10 $\mu g/m^3$ increase of $PM_{2.5}$. This study selected domestic CRFs and avoided regional differences of data as much as possible. CRF estimates rely on the quality of epidemiological studies. To avoid error introduced by the particularities of individual studies, multiple CRFs were selected for one health endpoint and then combined together using the fixed effect method. Meanwhile, in the evaluation process, the mean value and 95% CI of health outcomes were used to reflect the error range.

In the process of measuring health impact, uncertainty exists when using different unit values for monetization. The Chinese research and statistical data on the unit economic value for each health endpoint are relatively insufficient and the reported data are far less extensive than those of the United States. Uncertainty is unavoidable as a result of the limited domestic research available, since unit value varies greatly in the different regions and is generated by different monetization methods. Compared to WTP, HC and COI cannot fully reflect the disutility and welfare losses of the health impact, leading to underestimation of the unit economic value for health endpoints. This study obtained the unit value for Guangzhou by adjusting results of other cities in China with income per capita, to achieve accurate measurements.

3. Conclusions

The study provides an efficient method for using an integrated air quality attainment and evaluation system, including SMAT-CE and BenMAP-CE for health benefit analysis. The interpolation method eVNA was employed in SMAT-CE to generate more accurate air quality grid data by combining the spatial distribution of model results with observations. Based on the air quality grid data provided by SMAT-CE, BenMAP-CE can estimate the health impact and quantify the economic benefit with reasonable geographic spatial resolution. Then a comprehensive relationship between control measures and health outcomes can be found to help policy makers to optimize control strategy.

This paper demonstrates a real case study of assessing acute health effect results from air quality improvement during the Guangzhou Asian Games as an application of this integrated assessment system. Due to the strict

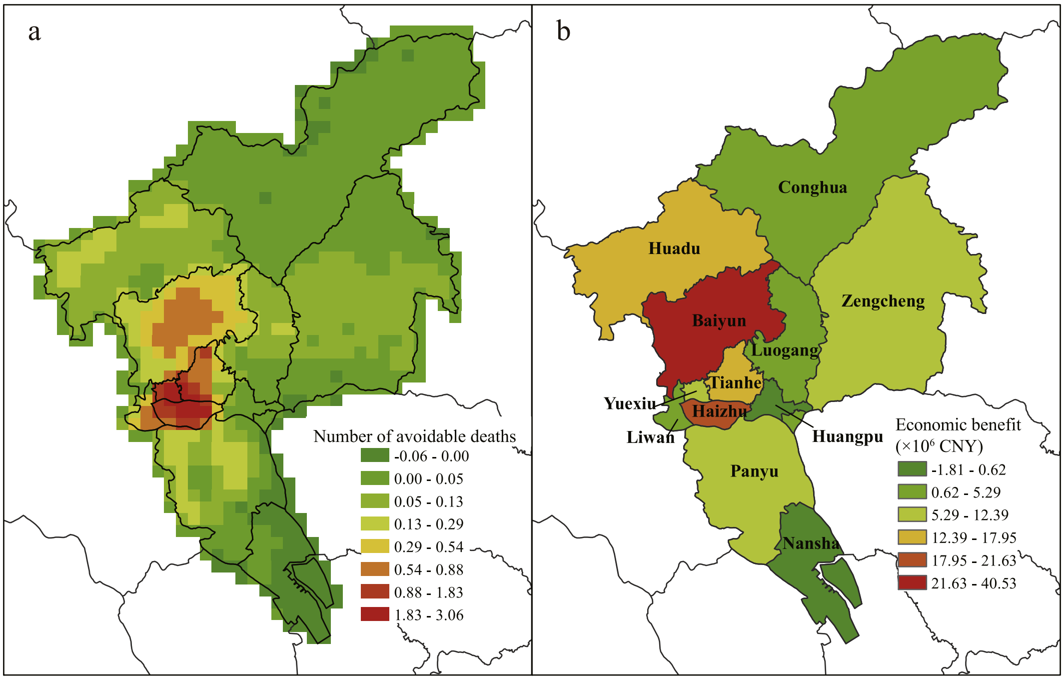

Fig. 7 – (a) Number of avoidable deaths and (b) economic benefit from all-cause mortality.

implementation of transportation restrictions and industrial emission control measures, the monthly average $PM_{2.5}$ concentration of November, 2010 in Guangzhou decreased by 3.5 $\mu g/m^3$ compared to the same period the previous year. The evaluation results showed that the air improvement resulted in 106.03 (95% CI, 43.97–161.81) annual premature avoidable deaths, and a total benefit of 165.45 (95% CI, 61.62–306.18) million CNY. Note that the benefit was underestimated because only air quality improvement in Guangzhou has been taken into account, while the air quality of other cities was also improved due to the joint regional air pollution control in the PRD. The public health benefit results can strongly encourage policy makers to implement more effective pollution control policies to decrease $PM_{2.5}$ emission. The presented software can aid in making strategic decisions for air pollution control in other cities in China or internationally as well (Fann et al., 2012).

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