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Research article

Health benefit assessment of PM<sub>2.5</sub> reduction in Pearl River Delta region of China using a model-monitor data fusion approachJiabing Li<sup>a</sup>, Yun Zhu<sup>a,\*</sup>, James T. Kelly<sup>b</sup>, Carey J. Jang<sup>b</sup>, Shuxiao Wang<sup>c</sup>, Adel Hanna<sup>d</sup>, Jia Xing<sup>c</sup>, Che-Jen Lin<sup>e</sup>, Shicheng Long<sup>f</sup>, Lian Yu<sup>a</sup><sup>a</sup> Guangdong Provincial Key Laboratory of Atmospheric Environment and Pollution Control, School of Environment and Energy, South China University of Technology, Guangzhou Higher Education Mega Center, Guangzhou 510006, China<sup>b</sup> US EPA, Office Air Quality Planning & Standards, Research Triangle Park, NC 27711, USA<sup>c</sup> State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Tsinghua University, Beijing 100084, China<sup>d</sup> Institute for the Environment, University of North Carolina at Chapel Hill, NC 27517, USA<sup>e</sup> Department of Civil and Environmental Engineering, Lamar University, Beaumont, TX 77710, USA<sup>f</sup> Guangzhou Urban Environmental Cloud Information Technology R&D Co.Ltd, Guangzhou 511400, China

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## ABSTRACT

The Pearl River Delta (PRD), one of the most polluted and populous regions of China, experienced a 28% reduction in fine particulate matter (PM<sub>2.5</sub>) concentration between 2013 (47 μg/m<sup>3</sup>) and 2015 (34 μg/m<sup>3</sup>) under a stringent national policy known as the Air Pollution Prevention and Control Action Plan (hereafter Action Plan). In this study, the health and economic benefits associated with PM<sub>2.5</sub> reductions in PRD during 2013–2015 were estimated using the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) software. To create reliable gridded PM<sub>2.5</sub> surfaces for BenMAP-CE calculations, a data fusion tool which incorporates the accuracy of monitoring data and the spatial coverage of predictions from the Community Multiscale Air Quality (CMAQ) model has been developed. The population-weighted average PM<sub>2.5</sub> concentration over PRD was predicted to decline by 24%. PM<sub>2.5</sub>-related mortality was estimated to decrease by more than 3800 due to decreases in stroke (48%), ischemic heart disease (IHD) (35%), chronic obstructive pulmonary disease (COPD) (10%), and lung cancer (LC) (7%). A 13% reduction in PM<sub>2.5</sub>-related premature deaths from these four causes yielded a large economic benefit of about 1300 million US dollars. Our research suggests that the Action Plan played a major role in reducing emissions and additional measures should be implemented to further reduce PM<sub>2.5</sub> pollution and protect public health in the future.

## 1. Introduction

Exposure to ambient fine particulate matter with aerodynamic diameter less than 2.5 μm (PM<sub>2.5</sub>) has been associated with adverse human health effects including mortality (Crouse et al., 2015; Di et al., 2017a, 2017b; Künzli et al., 2005; Pope et al., 2002) and has attracted substantial attention in China due to the extremely high PM<sub>2.5</sub> concentrations (Huang et al., 2014; Jung et al., 2009; Lv et al., 2017; van Donkelaar et al., 2016; Xing et al., 2017). To reduce PM<sub>2.5</sub> pollution, Chinese State Council has implemented air pollution control policies including Air Pollution Prevention and Control Action Plan (hereafter Action Plan; <http://www.gov.cn>) that aims to reduce emissions from power plants, industrial boilers, motor vehicles and fugitive dust. As reported in the Bulletin of Environmental Status, the average PM<sub>2.5</sub> concentration at monitors in the Pearl River Delta (PRD) region

decreased from 47 μg/m<sup>3</sup> in 2013 to 34 μg/m<sup>3</sup> in 2015 (Ministry of Environmental Protection of China. <http://www.mep.gov.cn>). This rapid decline in PM<sub>2.5</sub> resulted in the PRD region achieving China's national air quality goal of 35 μg/m<sup>3</sup> two years ahead of the Action Plan schedule.

Policy analysts commonly rely on health benefit evaluation tools that incorporate concentration-response (C-R) functions from epidemiologic studies to assess the health benefits of air quality improvements (Maji et al., 2018; Pascal et al., 2013; U.S.EPA, 2009). In particular, the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) developed by U.S. EPA has been widely used to estimate health benefits at the local, regional, national and global scale (Chen et al., 2017; Kheirbek et al., 2014; Sacks et al., 2018; Voorhees et al., 2014). BenMAP-CE provides three options to evaluate the cost burden of disease based on common monetary

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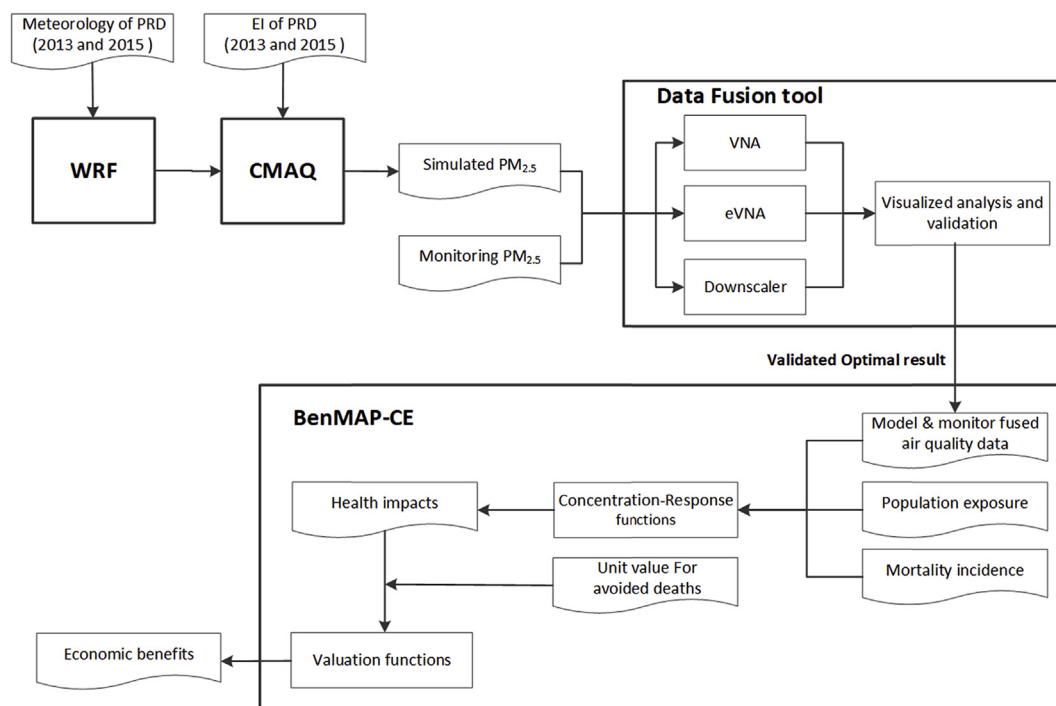


Fig. 1. Conceptual framework for model-monitor data fusion and health benefits estimate. EI: emission inventory.

methods: willingness to pay (WTP), cost of illness (COI), and the human capital approach (HC). The WTP approach comprehensively measures the amount of money people are willing to pay for reduction in the risk of illness. The COI approach is used to measure the cost associated with health endpoints, such as 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 (Yin et al., 2017, 2018). WTP is widely used for evaluating PM<sub>2.5</sub>-related health benefits in China (Li et al., 2016; Lu et al., 2016) because it considers intangible losses, such as pain, suffering and other adverse effects due to illness. The reliability of BenMAP-CE estimates depends on the accuracy and suitability of information used in benefit calculations such as air quality exposure fields, C-R functions, and baseline incidence rates. In previous health benefit assessments in China, the PM<sub>2.5</sub> exposure fields used in BenMAP-CE calculations were mostly based on chemical transport model (CTM) simulations. Predictions of CTMs, such as the Community Multiscale Air Quality (CMAQ) model, have the advantage of providing complete spatial and temporal coverage but suffer from bias compared with measured concentrations. Conversely, monitoring networks provide accurate measurements of PM<sub>2.5</sub> but suffer from limited coverage compared with CTM simulations. The number of PM<sub>2.5</sub> monitoring sites in China has recently increased from 1450 in 2013 to 1604 in 2015 (<http://106.37.208.233:20035/>), but the monitoring network still provides limited spatial coverage for such a large area with diverse emission sources.

Methods that combine information from PM<sub>2.5</sub> monitoring networks with other data sources including CTMs have recently been developed to improve exposure characterizations for health studies. For instance, Di et al. (2016) used a neural network approach to combine information from data sources including monitoring, CTMs, land use, and satellite sensors to predict daily PM<sub>2.5</sub> concentrations across the continental U.S. from 2000 to 2012. PM<sub>2.5</sub> fields for the U.S. were also developed by Beckerman et al. (2013) using a hybrid approach incorporating information from monitors, land use, traffic, and satellite retrievals in combination with CTM predictions. Zhan et al. (2017) used a spatially explicit machine learning algorithm to predict PM<sub>2.5</sub> concentration fields across China based on PM<sub>2.5</sub> monitoring, satellite, and meteorological measurements. Lv et al. (2016) developed PM<sub>2.5</sub> fields

for North China using data from PM<sub>2.5</sub> monitors, satellites, and other sources (e.g., meteorological monitoring networks). These studies indicated that using hybrid models or multiple data sources could improve the accuracy of PM<sub>2.5</sub> prediction. Furthermore, cross-validation of PM<sub>2.5</sub> fields developed by multiple methods for regions in the U.S. have recently demonstrated the potential value of hybrid methods that combine information from CTMs with other data sources compared with directly using CTM output (Friberg et al., 2016; Huang et al., 2018). Both the strength of monitoring data's accuracy and CTM's spatial coverage can be integrated into prediction to reduce model biases and errors. Yet despite the advantages of combining monitor data with information from CTMs and other data sources, we are not aware of any studies that have applied air quality fields based on model-monitor fusion to estimate the benefits of air quality management in China.

In this study, we estimated the health and economic benefits associated with PM<sub>2.5</sub> reduction in the PRD region between 2013 and 2015 using gridded PM<sub>2.5</sub> fields developed by combining information from CMAQ modeling and China's monitoring network. Avoidable mortality associated with PM<sub>2.5</sub> reduction was estimated using BenMAP-CE with the integrated exposure-response (IER) model that provides C-R functions for the full range of ambient PM<sub>2.5</sub> concentrations (Apte et al., 2015; Burnett et al., 2014). To facilitate creation of the gridded PM<sub>2.5</sub> fields, we developed an innovative Data Fusion (DF) tool to derive spatial fields based on three algorithms commonly applied in benefit assessments: Voronoi Neighbor Averaging (VNA) (Gold et al., 1997), enhanced Voronoi Neighbor Averaging (eVNA) (Ding et al., 2016), and Downscaler (DS) (U.S.EPA, 2015, 2016). The DF tool provides advanced capabilities for visualization and cross-validation and is available for download upon request (<http://www.abacas-dss.com/abacas/Default.aspx>).

## 2. Methodology

An overview of the analysis process for estimating health and economic benefits is provided in Fig. 1. Briefly, the Weather Research and Forecasting (WRF) model was used to simulate meteorological conditions in 2013 and 2015 to drive CMAQ air quality simulations for the

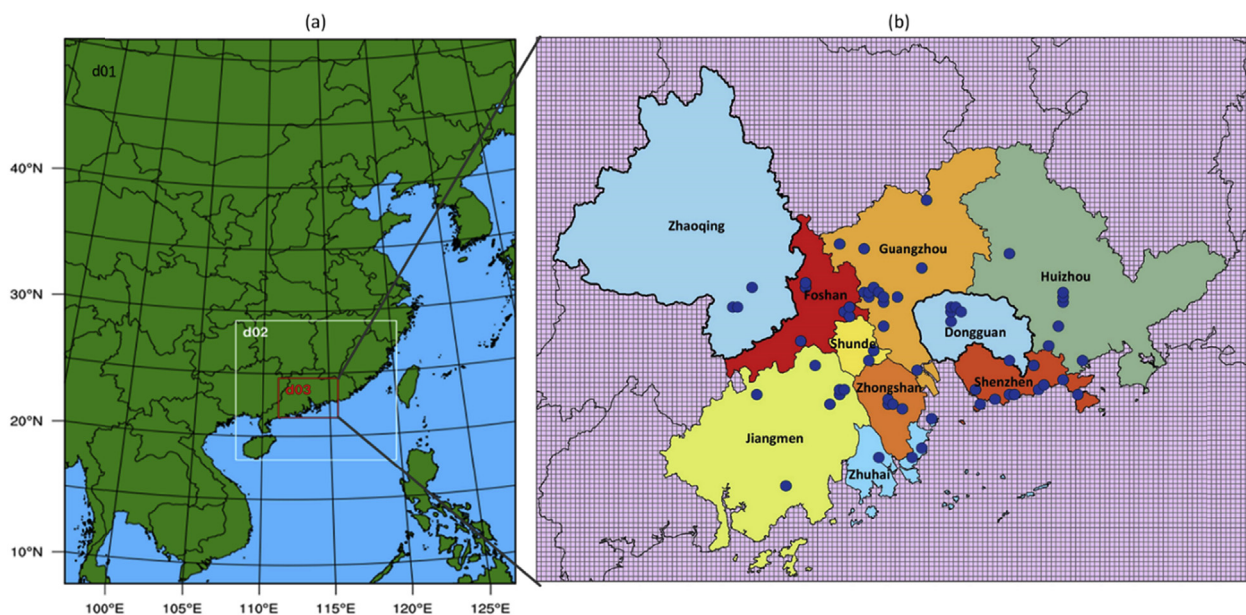


Fig. 2. (a) Nested simulation domains: 27 km (d01), 9 km (d02), and 3 km (d03); (b) Inner 3-km domain with monitor locations.

PRD region. Gridded PM<sub>2.5</sub> spatial fields for each year were then developed with the DF tool using the simulated and monitored PM<sub>2.5</sub>. Cross-validation (CV) was done to examine the performance of the methods, and the PM<sub>2.5</sub> fields considered most reliable for our application were selected for input to BenMAP-CE. Finally, BenMAP-CE was applied to estimate human health and economic benefits resulting from the PM<sub>2.5</sub> reductions using information on population, incidence rates, and unit value for avoided deaths. Further details on the process are provided below and in the [Supplementary Data](#).

2.1. Configuration of the WRF-CMAQ modeling system

The WRF-CMAQ modeling system used three nested modeling domains with horizontal resolutions of 27 km, 9 km and 3 km (Fig. 2a). The innermost 3-km domain covers the entire PRD region for which benefits were estimated (Fig. 2b). One-way nesting was used for meteorological simulations with WRF version 3.7 (<http://www2.mmm.ucar.edu/wrf>) and air quality simulations with CMAQ version 5.2 (<http://www.epa.gov/cmaq>). The initial and boundary conditions for the CMAQ simulation on the outer 27-km domain were based on default profiles in the CMAQ model. Boundary conditions for the middle 9-km and inner 3-km domains were generated from simulations on the outer and middle domains, respectively. The emission inventories for the outer and middle domains were provided by Tsinghua University, and the emission inventory for the inner 3-km domain was developed by the joint research team of Tsinghua University and South China University of Technology. Six pollutants were included in the inventories: SO<sub>2</sub>, NO<sub>x</sub>, CO, PM<sub>10</sub>, PM<sub>2.5</sub> and volatile organic compounds (VOCs). Pollutant emissions decreased in the inventories between 2013 and 2015 by 57% (SO<sub>2</sub>), 13% (NO<sub>x</sub>) and 28% (PM<sub>2.5</sub>). More details on emission inventories are provided in [Table S1](#) and [Table S2](#). PM<sub>2.5</sub> monitoring data over the PRD region were obtained from the Chinese Guangdong Environment Information Issuing Platform (<http://www.gdep.gov.cn/>).

Table 1  
Comparison between monitoring data and CMAQ simulation of PM<sub>2.5</sub> across all monitoring sites.

Year	obs_avg (μg/m <sup>3</sup> )	model_avg (μg/m <sup>3</sup> )	N <sup>a</sup>	Bias (μg/m <sup>3</sup> )	NME (%)	NMB (%)	R
2013	46.7	47.7	364	1.0	22.9	2.1	0.83
2015	34.2	28.0	332	-6.2	27.8	-18.1	0.86

Note: NME and NMB is defined in [Supplementary Data Section S1](#); obs\_avg — average observed value; model\_avg — average model value.

The monitoring sites are concentrated in the central urban area of PRD due to the high population, and outlying suburban areas are sparsely monitored due to the low population. The implications of the monitoring network design for our study are discussed below.

The performance of the WRF model was evaluated by comparing hourly mean predicted and measured values at the Sugang and Ronggui monitoring sites. The average Pearson correlation coefficient (R) and Index of Agreement (IOA) for wind speed were about 0.5 or greater at the sites, but wind speeds were biased high (normalized mean bias, NMB: 169%) at Sugang. For relative humidity and temperature, R and IOA were greater than 0.8. For CMAQ predictions of daily mean PM<sub>2.5</sub>, the correlation coefficient was 0.83 in 2013 and 0.86 in 2015, and predictions were slightly biased high in 2013 (NMB: 2.1%) and low in 2015 (NMB: -18.1%) ([Table 1](#)). The model performance statistics indicate that the WRF-CMAQ system had acceptable performance for our application based on consideration of statistics for CTM modeling in the U.S. ([Emery et al., 2017](#)) and our use of data fusion methods to reduce model biases and errors.

2.2. Estimating PM<sub>2.5</sub> with the data fusion tool

Annual average gridded PM<sub>2.5</sub> fields with 3-km horizontal resolution were developed for 2013 and 2015 over the PRD region based on algorithms of VNA, eVNA and DS using the DF tool. VNA calculates the concentration at the center of each grid cell as the inverse-distance-squared weighted average of PM<sub>2.5</sub> concentrations at neighboring monitors ([U.S.EPA, 2017](#)), where the neighboring monitors are identified using Delaunay triangulation. In the eVNA approach, the monitored concentrations used in VNA interpolation are multiplied by the ratio of the modeled concentration in the target grid cell to that in the monitor-containing grid cell ([Ding et al., 2016](#)). Therefore eVNA places strong weight on CMAQ gradients between the target cell and cells with nearby monitors. The DS model is a relatively complex statistical



prediction model, but DS resembles a simple linear regression model with spatially varying coefficients at a high level. DS uses Markov chain Monte Carlo (MCMC) methods with Gibbs sampling to develop a relationship between observed and modeled concentrations, and then uses the relationship to predict concentrations at points in the spatial domain (Berrocal et al., 2010a,b; Rundel et al., 2015). The DS model is frequently applied in health studies (Bravo et al., 2016; Breitner et al., 2016; Warren et al., 2013). More details on the algorithms of VNA, eVNA and DS are provided in the Supplementary Data Section S2.

The annual average PM<sub>2.5</sub> fields were calculated as the average of fields developed for each of the four calendar quarters. The skill of the PM<sub>2.5</sub> prediction models was evaluated using random ten-fold CV for predictions of quarterly average concentrations. Specifically, all monitoring sites were randomly divided into groups containing 10% or 90% of the sites. Each algorithm was then applied using data from 90% of the monitoring sites to predict PM<sub>2.5</sub> at the remaining 10%. This process was repeated for all groups so that predictions could be evaluated against measurements at all sites. Performance was characterized using root mean square error (RMSE) and R<sup>2</sup> statistics as defined in Section S1. As in other recent studies (Di et al., 2016), we refer to R<sup>2</sup> calculated for cases including multiple samples over all sites as the total R<sup>2</sup>.

### 2.3. Evaluating health and economic benefits attributable to PM<sub>2.5</sub> reductions

BenMAP-CE v1.3 was applied to evaluate the health and economic benefits of the PM<sub>2.5</sub> reductions in the PRD region between 2013 and 2015. The BenMAP-CE calculations are based on three key elements: (1) PM<sub>2.5</sub> fields for exposure characterization, (2) C-R functions and baseline incidence rates for health impact estimation, and (3) a unit value for willingness to pay (WTP) economic benefit estimation.

As discussed above, 3-km gridded PM<sub>2.5</sub> fields for 2013 and 2015 were developed using VNA, eVNA and DS methods with the DF tool. Population-weighted average PM<sub>2.5</sub> concentrations were calculated from these fields using population data from the 2010 China census provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn>). The 2010 census is the most recent and accurate national census and provides data at 1-km resolution that was mapped to the 3-km PM<sub>2.5</sub> grid for this study. Aggregated PM<sub>2.5</sub> concentrations referred to below are population-weighted values.

C-R functions were used to estimate PM<sub>2.5</sub>-related health impacts in BenMAP-CE as is commonly done in human health risk assessments (Fann et al., 2013; Voorhees et al., 2011). Since previous studies have reported that mortality contributes > 90% of the health impacts of air pollution (U.S.EPA, 2011), premature mortality was selected to represent the health impacts of air pollution control in our study. The integrated exposure-response model (IER model), which provides C-R functions for the full range of ambient PM<sub>2.5</sub> concentrations (Burnett et al., 2014), was applied to estimate the avoidable mortality related to PM<sub>2.5</sub> reduction for adults (age ≥ 25) (Xujia et al., 2015). The four leading causes of death in the IER model were selected for our application: lung cancer (LC), chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), and stroke. The C-R functions for these health endpoints are the same (Equations (1) and (2)), but

different parameter values are used based on the relevant studies (Table 2).

The relative risk (RR) of mortality for each health endpoint can be defined by Equation (1),

$$RR(C) = \begin{cases} 1 + \alpha(1 - e^{-\gamma(C-C_0)^\delta}), & \text{if } C > C_0 \\ 1, & \text{if } C \leq C_0 \end{cases} \quad (1)$$

where C is the average PM<sub>2.5</sub> concentration in 2013 or 2015; C<sub>0</sub> is the endpoint-specific counterfactual concentration for minimum-risk to PM<sub>2.5</sub>; and α, γ, and δ are parameters that define the shape of the C-R curves as presented in Table 2. The premature mortality, M<sub>e,g</sub>(C<sub>g</sub>), for each endpoint (e) associated with PM<sub>2.5</sub> in grid cell g was calculated using the RR values for 2013 and 2015 as follows:

$$M_{e,g}(C_g) = B_e \cdot P_g \cdot \frac{RR_e(C_g) - 1}{RR_e(C_g)} \quad (2)$$

where B<sub>e</sub> represents the baseline endpoint-specific mortality incidence in the PRD region in 2013, P<sub>g</sub> represents population in grid cell g, and RR<sub>e</sub>(C<sub>g</sub>) is the relative risk of endpoint e for concentration C<sub>g</sub> in grid cell g. Baseline incidence rates for the health endpoints were based on Xujia et al. (2015), which referred to governmental statistics from the Guangdong Provincial Health Statistical Yearbook (2013), and population distributions were based on the 2010 China census as described above.

The economic benefits associated with the health impact estimates were quantified using the WTP method. The unit value for avoided premature deaths was based on Xie (2011), and was adjusted by the Consumer Price Index (CPI) and exchange rate with US dollars using the 2010 currency year.

## 3. Results and discussion

### 3.1. Model validation and comparisons

PM<sub>2.5</sub> predictions of CMAQ were evaluated by direct comparison with measurements, and the VNA, eVNA and DS predictions were evaluated using ten-fold CV as summarized in Table 3 and Fig. S1. The three DF tool algorithms had higher R<sup>2</sup> and lower RMSE than CMAQ in both 2013 and 2015. The high R<sup>2</sup> values for the DF tool algorithms were due to the high density of monitoring sites in the urban area. VNA, eVNA and DS had lower R<sup>2</sup> values in 2015 than 2013, whereas CMAQ predictions had higher R<sup>2</sup> in 2015 than 2013. Model performance differences for the years could be related to the movement of industrial point sources from the densely monitored urban area to the sparsely monitored suburban area between 2013 and 2015 (<http://www.gdep.gov.cn/>; Fig. 3). Although the productivities of industrial sources improved during this period, the PM<sub>2.5</sub> filtration efficiency was relatively constant and led to increases in PM<sub>2.5</sub> emissions in parts of the suburban area between 2013 and 2015. The better performance for CMAQ in 2015 suggests that model performance improves with distance from the largest emission sources. The change in bias in CMAQ predictions from 2013 (NMB: 4.8%) to 2015 (NMB: -18.4%) would lead to an overestimate of the PM<sub>2.5</sub> change between these years. Compared with CMAQ predictions, the NMBs for the three DF tool algorithms were

**Table 2**  
Parameters used in evaluation of health impacts and economic benefits.

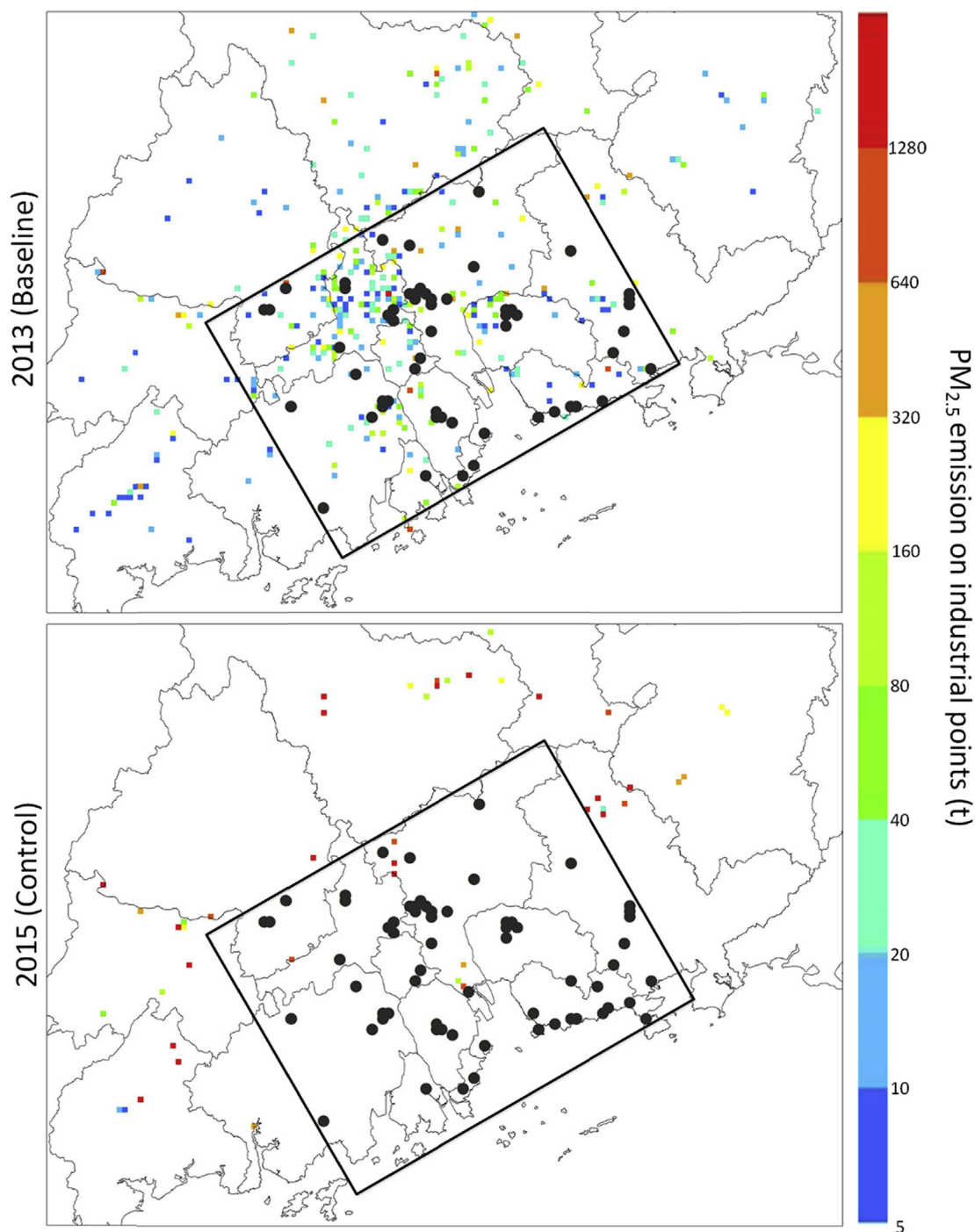
	Health endpoints	α	γ	δ	C <sub>0</sub>	Baseline incidence	References
Health impacts	IHD	0.83	0.0717	0.5516	6.96	0.001212	(Burnett et al., 2014) and (Xujia et al., 2015)
	Stroke	1.01	0.0174	1.1244	8.38	0.000769	
	COPD	29.00	0.0005938	0.6786	7.17	0.0003	
	LC	33.49	0.00005013	1.0128	7.24	0.000356	
	Economic benefits	Method	Value (thousand US dollars)			References	
	WTP	247			Xie (2011)		

**Table 3**  
Comparison of model performance statistics for CMAQ, VNA, eVNA and DS using ten-fold cross validation.

Performance	2013				2015			
	CMAQ	VNA	eVNA	DS	CMAQ	VNA	eVNA	DS
total R <sup>2</sup>	0.63	0.90	0.86	0.89	0.70	0.86	0.82	0.83
RMSE	13.1	6.0	7.4	6.3	9.8	4.2	4.9	4.7
NMB (%)	4.8	1.4	-2.1	1.4	-18.4	0.7	-0.6	0.3
slope	0.89	0.92	0.95	0.91	1.01	0.89	0.90	0.83

small and relatively constant between years.

Spatial distributions of annual PM<sub>2.5</sub> for the four approaches are illustrated in Fig. 4. For 2013, CMAQ predicts sharp gradients between high PM<sub>2.5</sub> concentrations in the central urban area and relatively low concentrations in the surrounding suburban area. In contrast, CMAQ predicts relatively low PM<sub>2.5</sub> in the central urban area and high concentrations near point sources in the suburban area in 2015 consistent with the emission fields (Fig. 3). The PM<sub>2.5</sub> spatial patterns for the VNA fields seem unrealistic in the suburban areas due to the extrapolation of measured values from the central monitored area to the surrounding unmonitored area. This degradation in performance away from monitors demonstrates the need to incorporate other data sources for



**Fig. 3.** PM<sub>2.5</sub> emissions of industrial point sources in 2013 and 2015. Note: Black circles represent the monitoring sites; Regions beyond the rectangle are unmonitored suburban parts of the PRD.

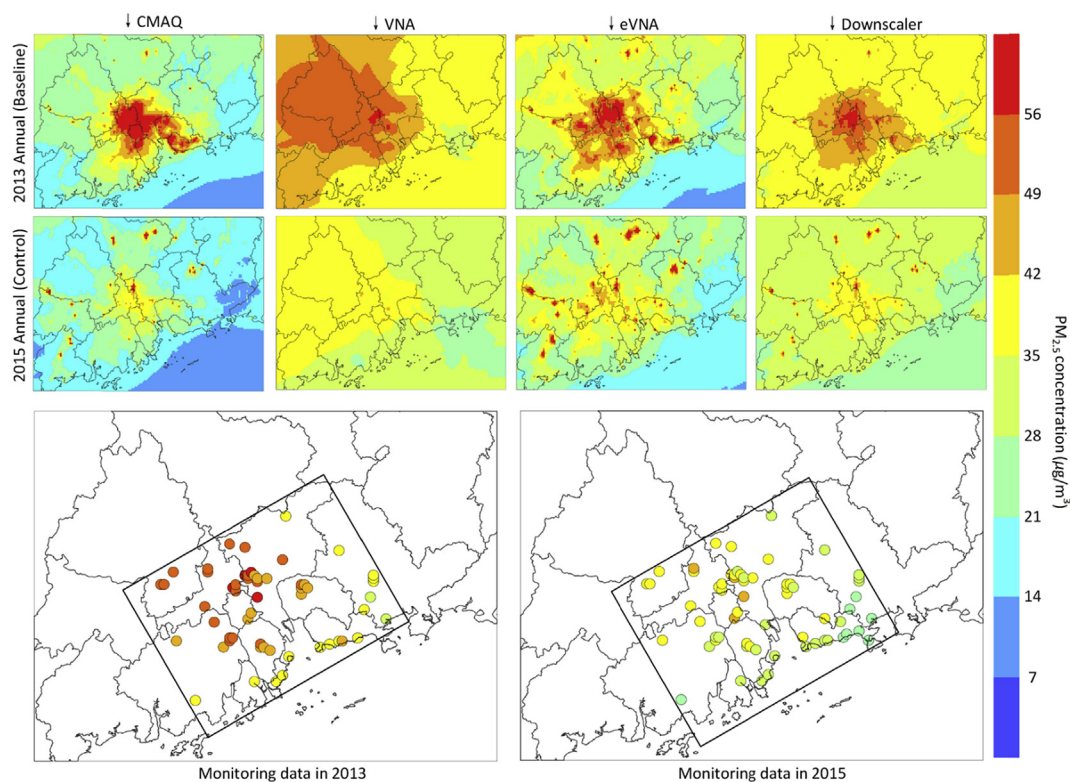


Fig. 4. Spatial distribution of CMAQ, VNA, eVNA and DS, and monitoring data. Note: Circles represent the monitoring sites; Regions beyond the rectangle are unmonitored suburban parts of the PRD.

predictions in sparsely or unmonitored areas. For the eVNA fields, relatively sharp gradients are evident compared with the other fields. These gradients are consistent with eVNA's algorithm, which applies weights based on ratios of CMAQ predictions in different spatial locations. eVNA's gradients may be beneficial in well monitored areas where emissions are well characterized but could be unreliable in unmonitored parts of the domain, and they cannot be verified in suburban areas due to the lack of monitoring. Overall, DS predictions appear to be most reliable for our application. DS performs well in CV for the central monitored area, and predictions are smooth but retain features of the CMAQ simulation in areas where monitors are not available for CV. Also, since the DS formulation does not directly involve interpolation of monitored concentrations, DS is conceptually sounder than VNA or eVNA where monitors are lacking. Therefore, DS predictions were used in our primary health benefit calculations, and CMAQ predictions were also applied to characterize the sensitivity of results to the use of data fusion.

### 3.2. Predicted $PM_{2.5}$ exposure level

DS predictions of changes in  $PM_{2.5}$  in the PRD region between 2013 and 2015 under the Action Plan are displayed in Fig. 5. Reductions in  $PM_{2.5}$  ranged from  $-10$  to  $26 \mu\text{g}/\text{m}^3$  over grid cells, and the population-weighted average  $PM_{2.5}$  concentration decreased from  $45 \mu\text{g}/\text{m}^3$  to  $34 \mu\text{g}/\text{m}^3$  (a 24% reduction) (Fig. 5a). The decrease in  $PM_{2.5}$  predicted by DS was confirmed by the monitoring data, for which the annual mean  $PM_{2.5}$  concentration decreased from  $47 \mu\text{g}/\text{m}^3$  to  $34 \mu\text{g}/\text{m}^3$  during the same period. The largest  $PM_{2.5}$  reductions were observed in the most polluted regions, such as Foshan and Shenzhen. The reduction in population-weighted average  $PM_{2.5}$  aggregated by city is shown in Fig. 5b. During 2013 to 2015,  $PM_{2.5}$  concentration decreased in all cities, with reductions greater than  $10 \mu\text{g}/\text{m}^3$  in Foshan, Shunde, Guangzhou, Shenzhen, Jiangmen and Zhongshan. Considering the  $PM_{2.5}$  reductions and their spatial consistency with the change in

anthropogenic emissions, the results suggest that implementation of the Action Plan played a major role in improving air quality in the PRD region.

### 3.3. Mortality reduction and economic benefit evaluation related to $PM_{2.5}$ concentration

We estimated health benefits for the four leading causes of  $PM_{2.5}$ -related premature mortality (IHD, stroke, COPD and LC). We estimated that there were about 29,600  $PM_{2.5}$ -related premature adult deaths due to these four causes in the PRD region in 2013. Therefore, about 11% of the number of adult deaths in the PRD region were estimated to be associated with these  $PM_{2.5}$ -related health endpoints in 2013. IHD, stroke, COPD and LC contributed 45%, 44%, 7% and 4%, respectively, to the premature mortality estimate (Fig. 6a). In 2013,  $PM_{2.5}$ -related mortality in Guangzhou, Shenzhen and Dongguan were over 4000, and the value in Guangzhou was close to 7000 (Fig. 6b).

Although the number of  $PM_{2.5}$ -related premature adult deaths from IHD, stroke, COPD, and LC were still substantial (about 25,700) in 2015, the reduction in  $PM_{2.5}$  from 2013 to 2015 led to about 3900 avoided  $PM_{2.5}$ -related adult deaths from these four causes. The reduction in mortality varied by endpoint consistent with the different C-R functions (Apte et al., 2015), with stroke and IHD accounting for about 48% and 35% of the avoided mortality, respectively (Fig. 6c). The decrease in premature mortality from stroke and IHD was only about 14% and 10%, respectively, due to the high baseline mortality rates of stroke and IHD in 2013.

$PM_{2.5}$ -related mortality reductions and economic benefits aggregated by city in 2013 and 2015 are shown in Fig. 6d. Shenzhen and Guangzhou achieved mortality reductions of about 1700 with economic benefits over 570 million US dollars. The mortality reductions and economic benefits for Shenzhen, Guangzhou, Dongguan, Foshan and Jiangmen accounted for over 75% of the improvements in the PRD region. In cities with more than 5 million residents (Table 4),

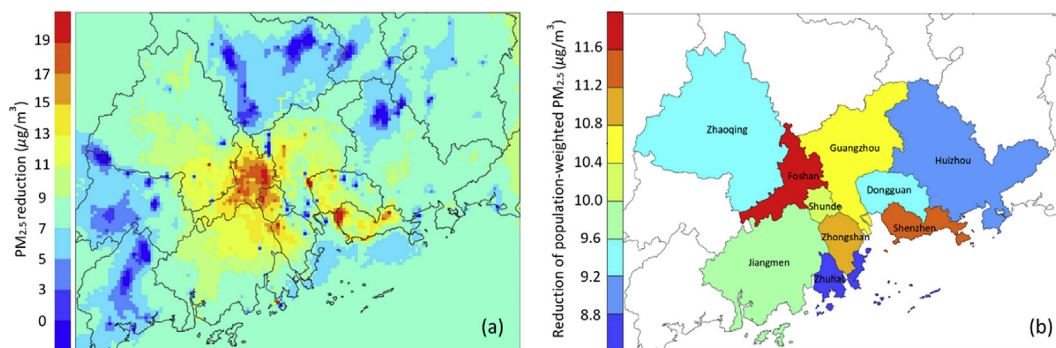


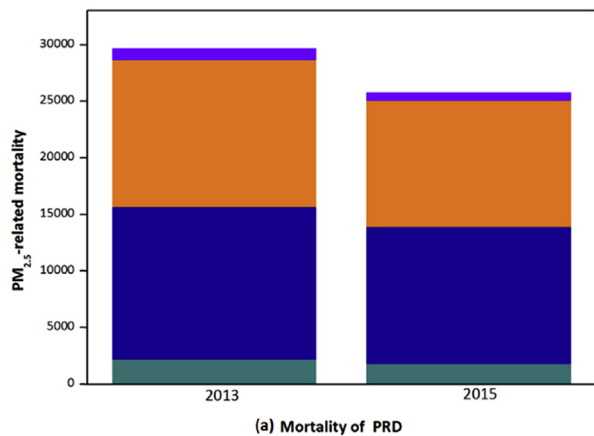
Fig. 5. (a) Spatial distribution of grid cell PM<sub>2.5</sub> population-weighted reduction; (b) spatial distribution of aggregated population-weighted PM<sub>2.5</sub> reduction.

population-weighted PM<sub>2.5</sub> concentration declined by over 24% on average, which led to a mortality reduction greater than 2200 and economic benefits of about 740 million US dollars. However, in cities with relatively small population (e.g., Shunde), the avoidable PM<sub>2.5</sub>-related mortality and economic benefits were limited (avoidable mortality < 150, economic benefit < 50 million US dollars) despite PM<sub>2.5</sub> reductions of 11 µg/m<sup>3</sup>. This pattern demonstrates the strong influence of population on the health impact evaluation.

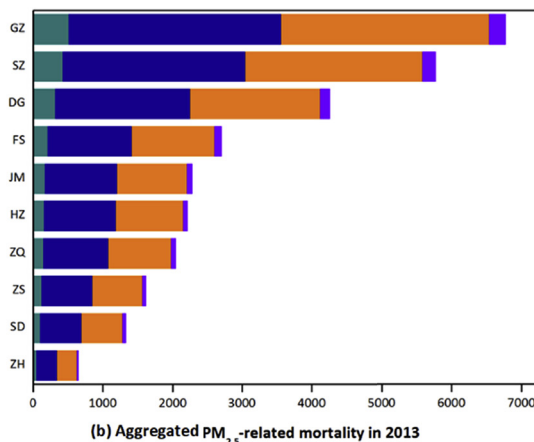
The percent reduction in PM<sub>2.5</sub> concentration is compared with the percent reduction in PM<sub>2.5</sub>-related mortality in Fig. 7. The relationship between percent reductions in PM<sub>2.5</sub> and PM<sub>2.5</sub>-related mortality varies

across cities. The highest PM<sub>2.5</sub> percent reduction was 29% in Foshan, where the estimated mortality reduction was 14%. Shenzhen achieved a higher percent reduction in PM<sub>2.5</sub>-related mortality (16%) than Foshan with a smaller percent decrease in PM<sub>2.5</sub> concentration (28%). Apte et al. (2015) indicated that avoided mortality estimated by the IER model increases sharply with PM<sub>2.5</sub> at low concentrations but increases gently at higher concentrations. Therefore the marginal health benefits (i.e. mortality abatement induced by unit reduction of PM<sub>2.5</sub> level) increases with declines in PM<sub>2.5</sub> concentrations in the model.

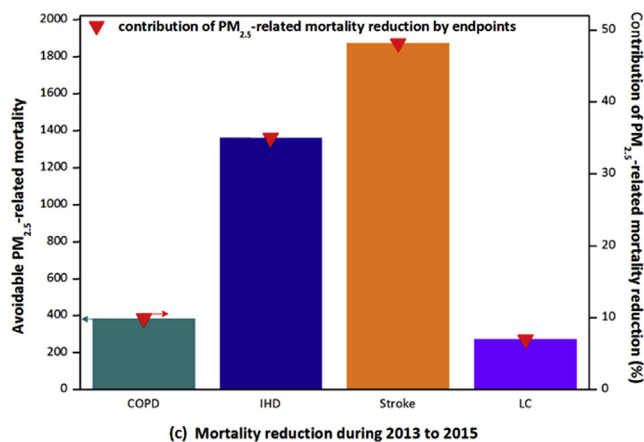
Although Shenzhen achieved a relatively high health benefit compared to other cities due to the dense population and considerable



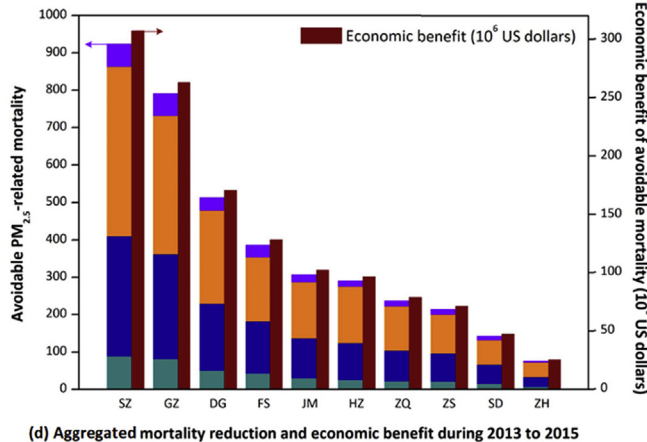
(a) Mortality of PRD



(b) Aggregated PM<sub>2.5</sub>-related mortality in 2013



(c) Mortality reduction during 2013 to 2015



(d) Aggregated mortality reduction and economic benefit during 2013 to 2015

LC mortality      Stroke mortality      IHD mortality      COPD mortality

Fig. 6. (a) PM<sub>2.5</sub>-related premature mortality of the PRD region in 2013 and 2015; (b) Aggregated PM<sub>2.5</sub>-related premature mortality in 2013; (c) PM<sub>2.5</sub>-related premature mortality and its contribution by endpoints during 2013–2015; (d) Aggregated avoidable premature deaths and economic benefits during 2013–2015.



**Table 4**  
Comparison of health benefits derived from air quality change calculated by DS, CMAQ and nearest-site approach.

City	Population (10 <sup>6</sup> )	Reduction of population-weighted PM <sub>2.5</sub> concentration (µg/m <sup>3</sup> )			Avoidable mortality			Economic benefit (10 <sup>6</sup> US dollars)		
		DS	CMAQ	Nearest-site	DS	CMAQ	Nearest-site	DS	CMAQ	Nearest-site
SZ	10.63	13.0	27.9	6.5	924	2149	528	307	714	175
GZ	12.93	11.2	22.5	13.4	791	1474	914	263	490	304
DG	8.32	9.9	19.0	8.8	514	1082	451	171	359	150
FS	4.80	16.5	29.0	15.2	386	610	363	128	203	121
JM	4.50	11.0	13.4	11.6	308	445	329	102	148	109
HZ	4.70	7.9	7.9	7.5	291	412	284	97	137	94
ZQ	4.02	9.5	7.6	13.8	237	253	291	79	84	97
ZS	3.17	11.5	16.5	12.7	215	344	245	72	114	82
SD	2.49	11.2	26.9	7.4	143	308	100	48	102	33
ZH	1.59	7.8	9.4	7.8	77	135	75	25	45	25
total	57.15	–	–	–	3886	7212	3580	1292	2396	1190

Note: SZ - Shenzhen, GZ - Guangzhou, DG - Dongguan, FS - Foshan, JM - Jiangmen, HZ - Huizhou, ZQ - Zhaoqing, ZS - Zhongshan, SD - Shunde, ZH - Zhuhai.

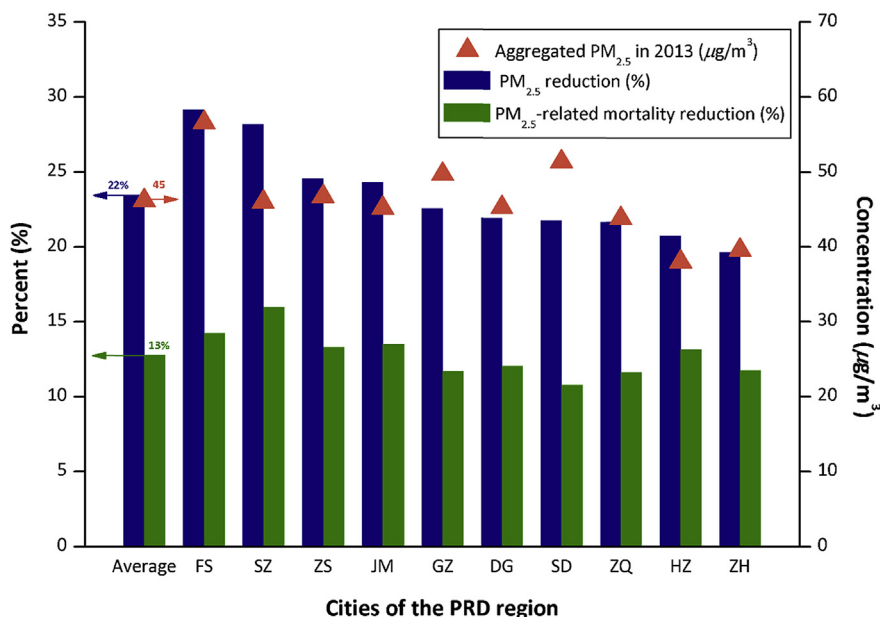
PM<sub>2.5</sub> reductions, its marginal health benefits (reduction of mortality) were only 560 (per 100 thousand). Moreover, marginal health benefits for Guangzhou, Foshan and Shunde were all less than 500 (per 100 thousand), and the annual average PM<sub>2.5</sub> concentrations in these cities were still over than the national air quality secondary standard (35 µg/m<sup>3</sup>) in 2015. Accordingly, the health benefits attributed to air quality improvement in the PRD region were still limited. For example, the World Health Organization (WHO) annual average PM<sub>2.5</sub> guideline to protect public health is 10 µg/m<sup>3</sup>, while China's secondary standard of 35 µg/m<sup>3</sup> corresponds to WHO's interim target. To achieve the WHO PM<sub>2.5</sub> target, current policies should remain in place and additional measures should be implemented (e.g., optimization of industrial structures and the adjustment of energy structures (Dai et al., 2016; Li et al., 2017)).

To examine the influence of model-monitor fusion on health benefit estimates, we compared benefits estimated using DS fields with those estimated using CMAQ and monitor-based fields. To develop the monitor-based fields, PM<sub>2.5</sub> concentrations in a grid cell were assigned the concentration of the nearest monitoring site as has been considered in previous studies (Baxter et al., 2013; Hodas et al., 2013) (Table 4). In PRD, the avoided mortality using DS fields was estimated at 3886, close to the estimate of Xujia et al. (2015), which assumed that annual average PM<sub>2.5</sub> concentration in PRD reached the national air quality secondary standard (35 µg/m<sup>3</sup>) in 2017 and applied the IER model to estimate the avoided deaths. The avoided mortality estimated using

CMAQ fields was over than 7200, nearly two times that based on DS. The difference in avoided mortality is due to the difference in bias of CMAQ predictions for 2013 and 2015 compared with the relatively consistent and small bias for DS predictions. Specifically, CMAQ predictions were biased high in 2013 and low in 2015, and so the reduction in PM<sub>2.5</sub> between the years and the associated benefits would be overestimated if CMAQ output were applied directly.

The avoided mortality estimated using the nearest-site concentration assignment was about 3500 with economic benefits of about 1200 million dollars (Table 4). Therefore, in aggregate, the nearest-site approach yielded avoided mortality estimates within about 10% of the DS-based estimates. However, the spatial pattern of health benefits differed considerably for the methods. For instance, Guangzhou achieved the highest health benefits in the nearest-site approach, but Shenzhen achieved the highest in DS. Avoided mortality estimates were 43% lower in Shenzhen for the nearest-site approach than for DS. The nearest-site approach likely underestimated concentrations in north-west Shenzhen where there are no monitors by using the relatively low concentrations measured at sites to the southeast. These limitations likely led to underestimates of avoided mortality in Shenzhen in the nearest-site approach.

Since CMAQ suffers from bias compared with measurements and the nearest-site approach provides limited spatial resolution, the model-monitor fusion approach used in this study provides a pragmatic approach to provide improved air quality surfaces for health impact



**Fig. 7.** Reduction of aggregated population-weighted PM<sub>2.5</sub> levels and reduction of PM<sub>2.5</sub>-related mortality between 2013 and 2015. Note: (1) Blue columns and Green columns represent reductions in PM<sub>2.5</sub> pollution and PM<sub>2.5</sub>-related mortality, respectively. Orange triangles is aggregated population-weighted PM<sub>2.5</sub> concentration in 2013. The first group of columns and triangle is the average values of all cities in the PRD region, and the other groups represent values of different cities. (2) FS - Foshan, SZ - Shenzhen, ZS - Zhongshan, JM - Jiangmen, GZ - Guangzhou, DG - Dongguan, SD - Shunde, ZQ - Zhaoqing, HZ - Huizhou, ZH - Zhuhai. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



assessments. More details of health benefits including VNA and eVNA are provided in Table S4.

### 3.4. Methodological uncertainties

There were several methodological uncertainties in our study. (1) The PM<sub>2.5</sub> monitoring sites are heavily concentrated in the central and southeastern parts of PRD, and the lack of monitoring in the suburban areas could limit the accuracy of predictions there. The overall benefit estimates should not be strongly influenced by these limitations though, considering that over 75% of the population was within about 10 km of a monitor and CMAQ predictions helped reduce uncertainty away from monitors. (2) The IER function was applied to estimate mortality reduction; however, the IER parameters were desired values based on 1000 simulations with 1000 sets of IER parameters from limited epidemiologic studies (Burnett et al., 2014; Xuji et al., 2015). Moreover, for stroke and IHD endpoints, the mortality reductions for adults (age ≥ 25) were estimated without age groupings, which can lead to slightly overestimated avoidable mortality (Burnett et al., 2014). (3) Baseline mortality incidence (BMI) data for 2013 was used for the entire analysis, because information on BMI variations between 2013 and 2015 is not available. (4) Population data was mapped to a 3 × 3 km grid to be consistent with the resolution of the gridded PM<sub>2.5</sub> fields, and population and PM<sub>2.5</sub> values in each grid cell were assumed to be independent and uniform. The uncertainty associated with these assumptions is believed to be small because 3-km resolution is relatively high compared with typical health impact assessments. Also, although people may have changed address between the 2010 census and the 2013–2015 study period, movement likely occurred in the core area of PRD without changing the overall population distribution. (5) Only the WTP method was used to evaluate economic benefits, and the unit value for monetization was based on studies in other regions (Xie, 2011), adjusted by CPI, due to the limited information available for the PRD region.

### 4. Conclusion

In this study, an innovative DF tool was developed and applied to create improved estimates of PM<sub>2.5</sub> distributions by combining the accuracy of monitoring data with the spatial coverage of CMAQ modeling. The model-monitor fused PM<sub>2.5</sub> fields were then used with BenMAP-CE to estimate the health impacts and economic benefits related to PM<sub>2.5</sub> reduction in the PRD region between 2013 and 2015. The study illustrates a pragmatic approach to produce improved air quality surfaces for health benefits evaluation and is the first application of BenMAP-CE to assess the health benefits associated with PM<sub>2.5</sub> reduction under the implementation of Action Plan in PRD, China.

PM<sub>2.5</sub> concentrations in the PRD region decreased by 24% between 2013 and 2015 according to a spatial pattern consistent with emission controls implemented under the Action Plan. This behavior suggests that the Action Plan played a major role in the air quality improvement. High levels of PM<sub>2.5</sub> observed in the central and southeastern parts of PRD in 2013 decreased by more than 10 µg/m<sup>3</sup> following the emission reductions. The avoided PM<sub>2.5</sub>-related premature mortality during 2013–2015 was estimated at 3886, which yielded an economic benefit of about 1300 million US dollars. However, the health benefits associated with the PM<sub>2.5</sub> reductions were still limited in the PRD region due to the relatively low marginal benefits under high PM<sub>2.5</sub> conditions. The health benefit estimates from this study strongly suggest that retain current policies and implement additional pollution control policies to further reduce PM<sub>2.5</sub> and protect public health.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2018.12.060>.

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